

MORPH: More Robust ASIC Placement for Hybrid Region Constraint Management

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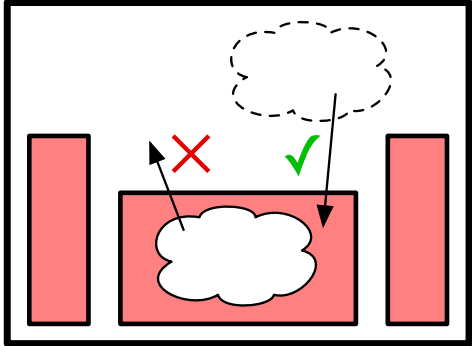
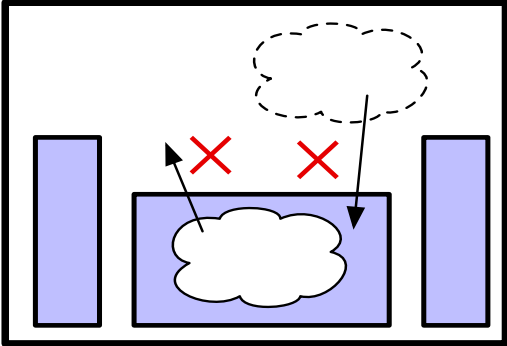
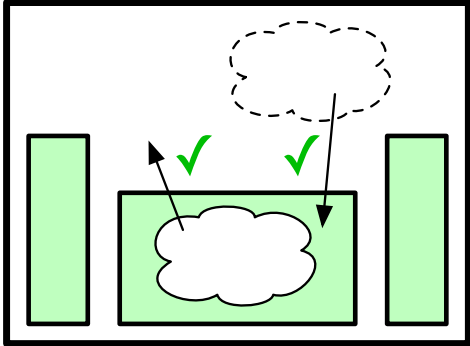
1. Introduction
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3. The MORPH Algorithm
4. Experimental Results
5. Conclusion & Future Work

Introduction

Region constraint in ASIC CAD

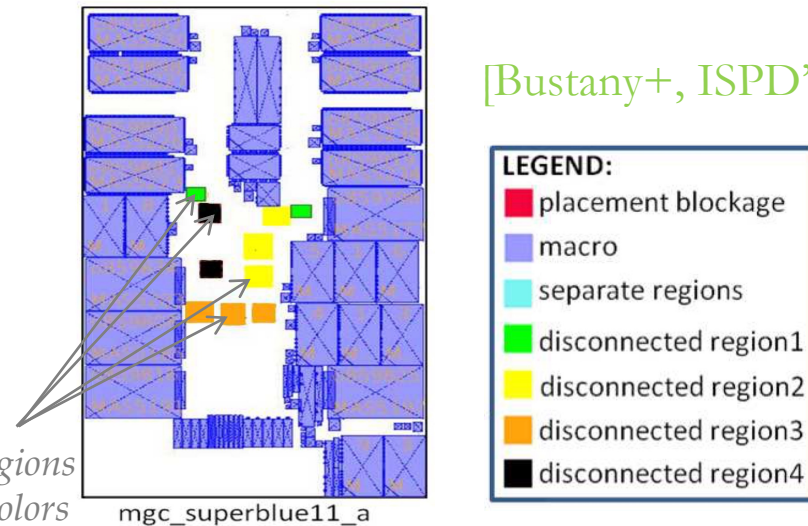
- ▶ An essential feature provided by modern ASIC CAD tools.
- ▶ Three categories of region constraints: **default regions**, **fence regions**, and **guide regions**.



Category	Default Region	Fence Region	Guide Region
			
hard / soft constraint?	Hard All cells subject to this constraint must be placed inside the region.	Hard All cells subject to this constraint must be <u>exclusively</u> placed inside the region.	Soft Other constraints such as wirelength, can override this soft constraint.

Space disconnectivity

- ▶ A region is made up of multiple spatially disjoint rectangular subregions.
- ▶ Fence-region-aware clustering technique. [Huang+, TCAD'17]
- ▶ Look-ahead region-aware rough legalization. [Darav+, TODAES'16] [Chow+, SLIP'17]
- ▶ Multi-electrostatics-based placement model. [Gu+, ICCAD'20]



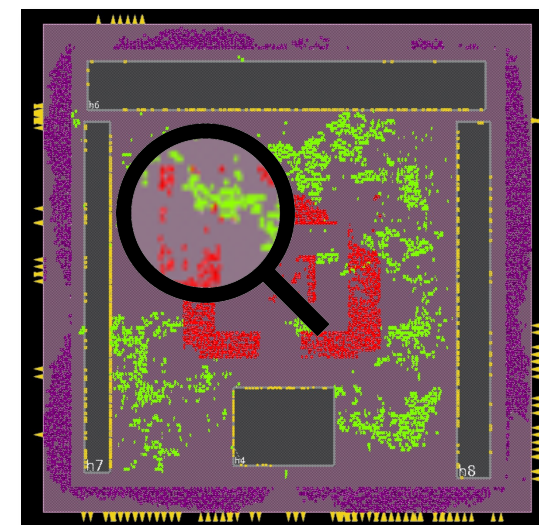
Four fence regions in different colors

Hybrid region constraints

- ▶ None of the previous work considered default regions or guide regions.
- ▶ Multi-functionality requirement.

Robustness issue

- ▶ Non-orthogonality for instances and their placeable areas (for default regions)
- ▶ Multi-region-aware placement can easily fall into local optimum and even diverge. [Gu+, ICCAD'20]



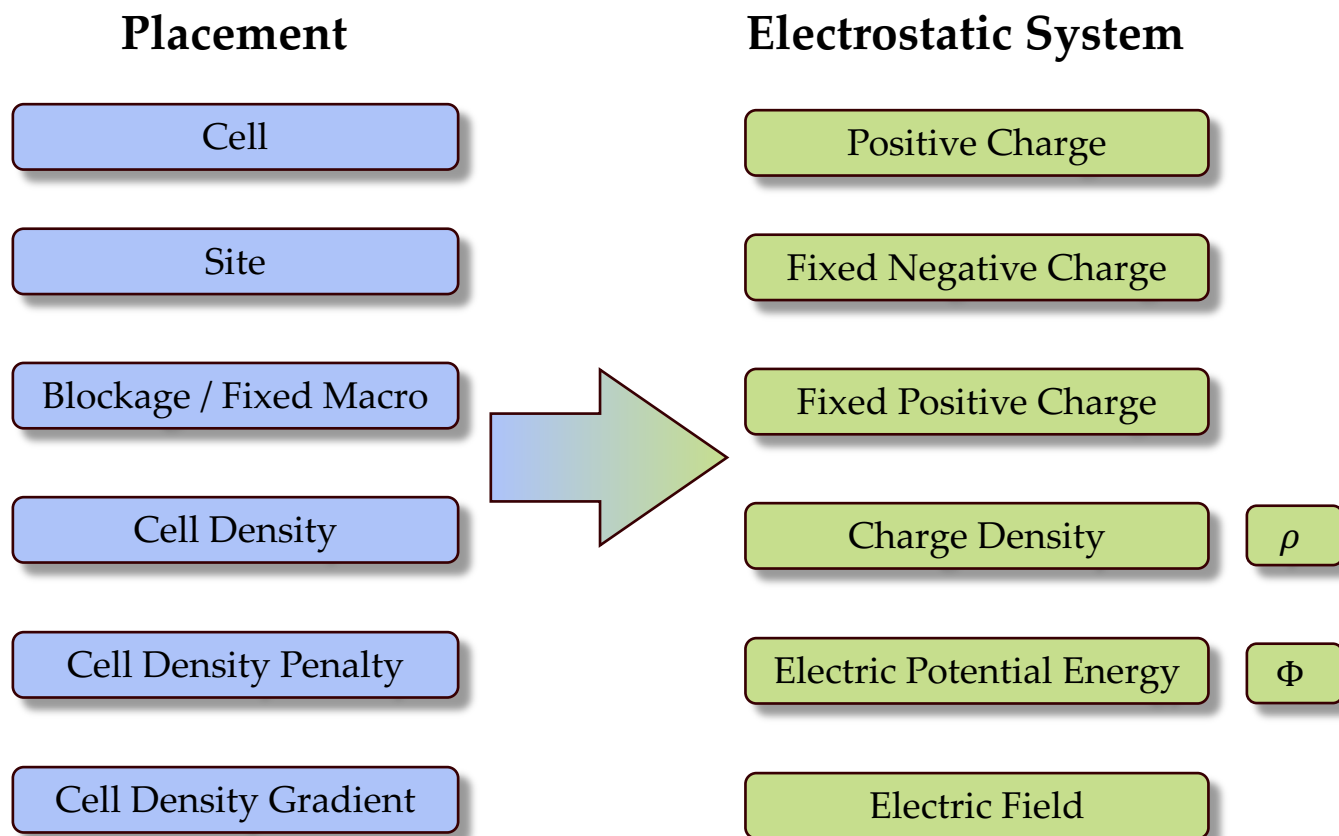
Non-orthogonality: Cells not subject to any default region constraint can be placed within default regions.

MORPH: a more robust multi-electrostatics-based placement algorithm for hybrid region constraints.

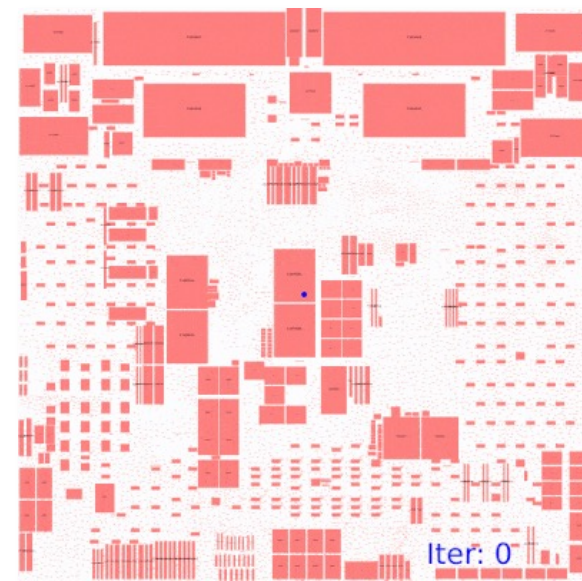
- ▶ shared electrostatics model → a **unified** electrostatics formulation for default regions and fence regions.
- ▶ A wirelength-prioritized penalty method → balanced guide region optimization without compromising wirelength minimization.
- ▶ A modified **Nesterov's accelerated LBFGS algorithm** with second-order information → significantly improve the solution quality and the stability with minor runtime overhead.
- ▶ Experimental results on the ISPD 2015 benchmarks [**Ismail+, ISPD'15**] demonstrate that our proposed algorithm can achieve **5.6-14.3% HPWL improvement** and **10-24% overflow reduction** when compared to other SOTA fence region-aware placers.

Preliminaries

Analogy between placement density and electrostatic system ePlace [Lu+, TCAD'15]



Charge Density Map Visualization



DREAMPlace [Lin+, DAC'19]

Optimize wirelength while adhering to multiple density constraints, [Gu+, ICCAD'20]

$$\begin{aligned} & \min_{x,y} \tilde{W}(x,y) \\ \text{s.t. } & \Phi_s(x^{(s)}, y^{(s)}) \leq \hat{\Phi}, \forall s \in S, \end{aligned}$$

where S is the set of electrostatic systems.

WAWL Wirelength Model

Weighted-average (WA) wirelength model $\tilde{W}(x,y)$ approximates half-perimeter wirelength (HPWL), [Ray+, DATE'13]

Augmented Lagrangian Method

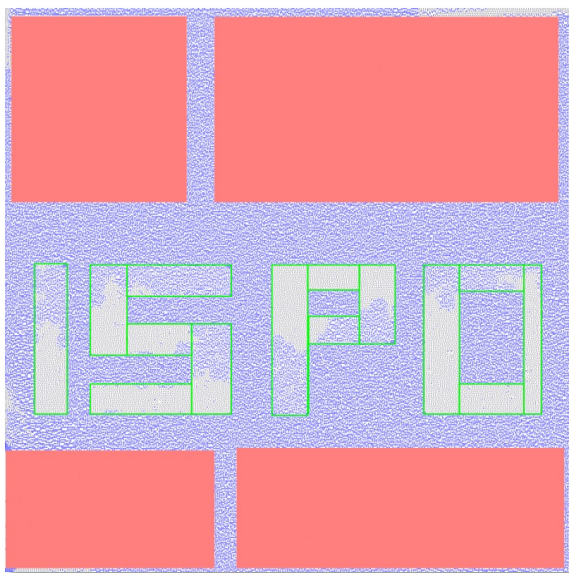
Transfer the constrained problem into an unconstrained one, [Zhu+, DAC'18]

$$\begin{aligned} & \min_{x,y} \tilde{W}(x,y) + \sum_{s \in S} \lambda_s \mathcal{D}_s \\ \text{s.t. } & \mathcal{D}_s = \Phi_s + \frac{1}{2} c_s \Phi_s^2, \forall s \in S. \end{aligned}$$

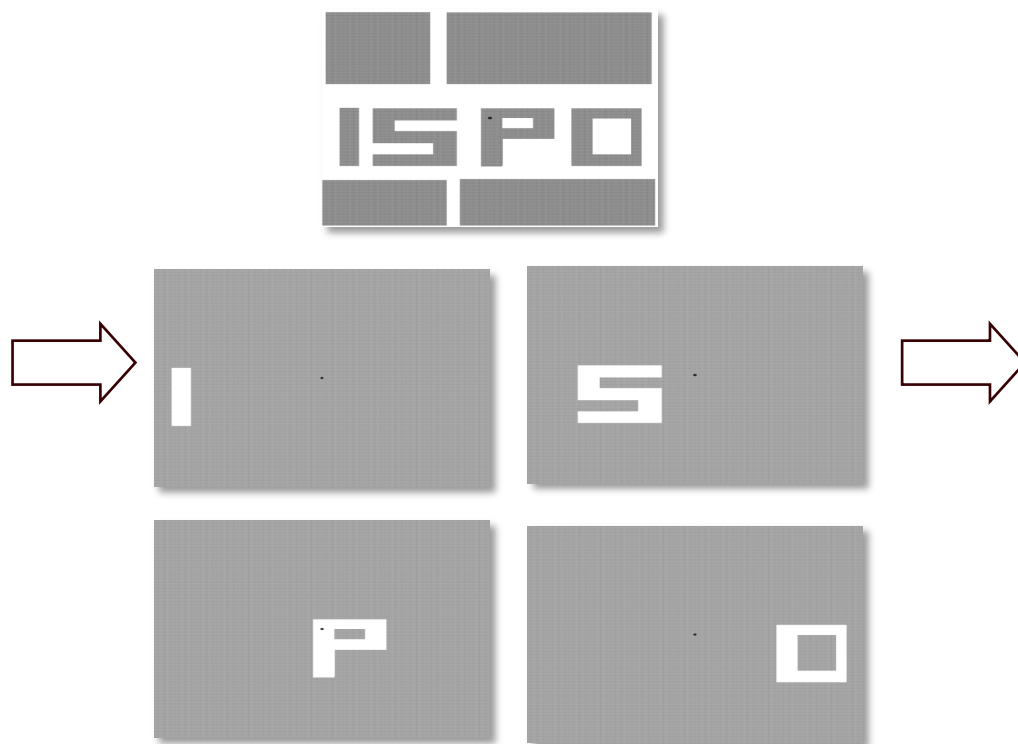
Multi-Electrostatics-based Density Model

- ▶ Each fence region has a separate electrostatic system.
- ▶ #electrostatic systems = 1 + #fence regions.
- ▶ Insert artificial blockages in each electrostatic system (ES) -> block illegal areas.

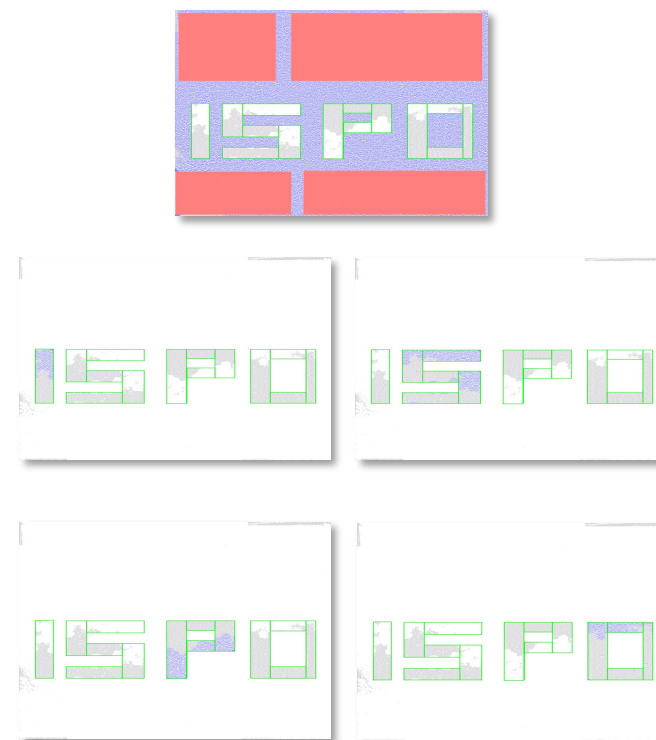
Placement



Artificial Blockages in each ES



Charge Density Map Visualization



* purple: cells, red: macros, gray: artificial blockages in each electrostatic system.

The MORPH Algorithm

Multi-electrostatics-based placement for hybrid regions

Minimize wirelength while subject to default regions, fence regions, and guide regions constraints,

$$\min_{\mathbf{x}, \mathbf{y}} \mathcal{L}(\mathbf{x}, \mathbf{y}) = \tilde{W}(\mathbf{x}, \mathbf{y}) + \sum_{k=0}^{K_1-1} \lambda_k \mathcal{D}_k + \sum_{k=K_1}^{K_1+K_2-1} \eta_k \Gamma_k(\mathbf{x}^{(k)}, \mathbf{y}^{(k)}),$$

$$\mathcal{D}_k = \Phi_k(\mathbf{x}^{(k)}, \mathbf{y}^{(k)}) + \frac{1}{2} \mathcal{C}_k \Phi_k^2(\mathbf{x}^{(k)}, \mathbf{y}^{(k)}),$$

▶ Default regions & fence regions: **shared electrostatic model**

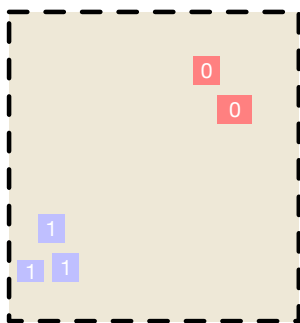
▶ Guide regions: **wirelength-prioritized penalty method**

Shared Electrostatics Model

- ▶ Formulate default regions and fence regions as a **unified** multi-electrostatics placement formulation.
- ▶ $\# \text{electrostatic systems} = 1 + \# \text{default regions} + \# \text{fence regions}$.

Example

Region Locations



Instance Group



Instances assigned to
Default Region 0



Instances assigned to
Fence Region 1



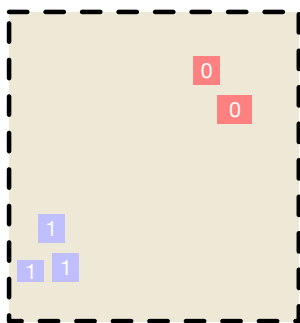
Instances without any
region constraint

Shared Electrostatics Model

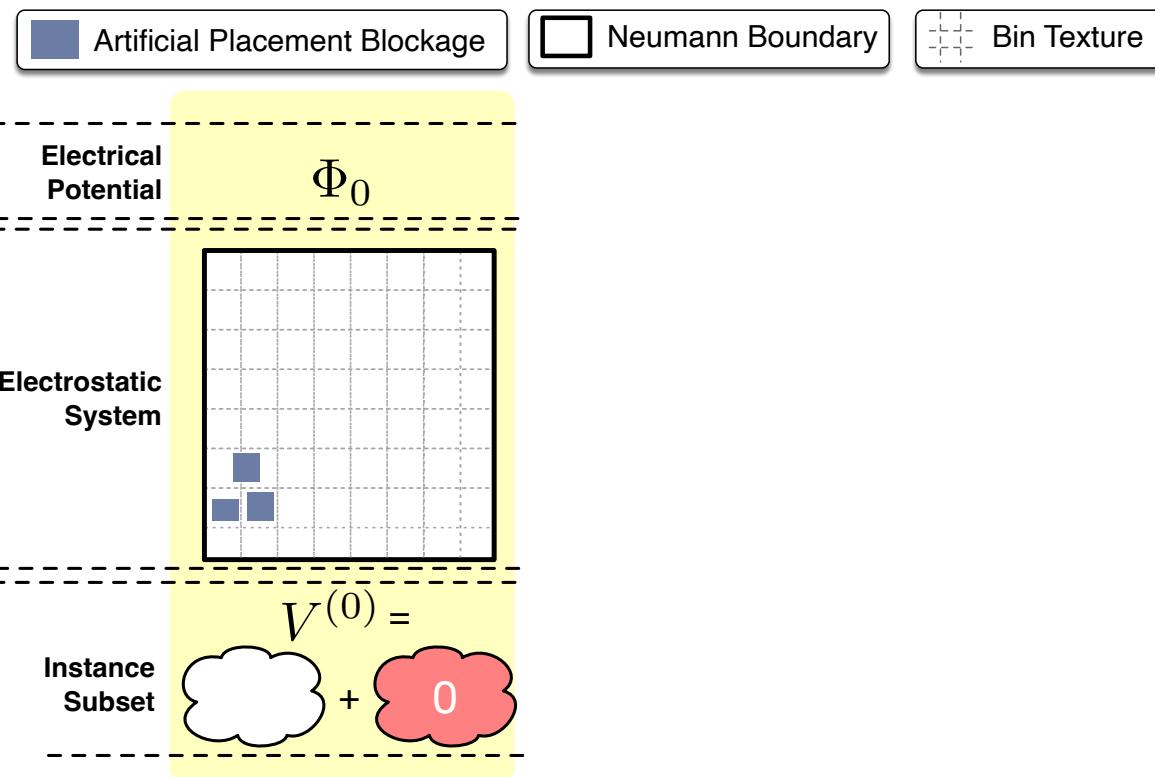
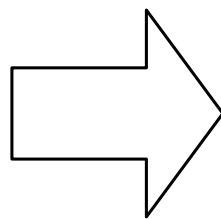
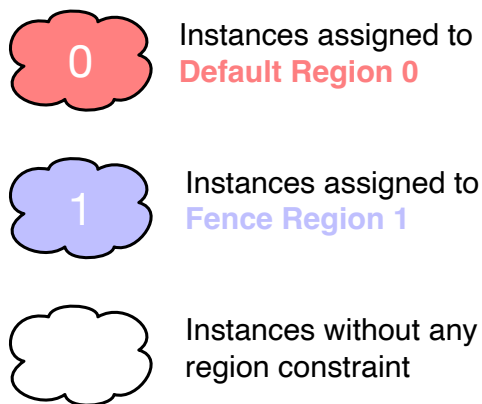
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Example

Region Locations



Instance Group

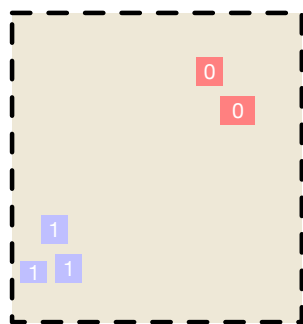


Shared Electrostatics Model

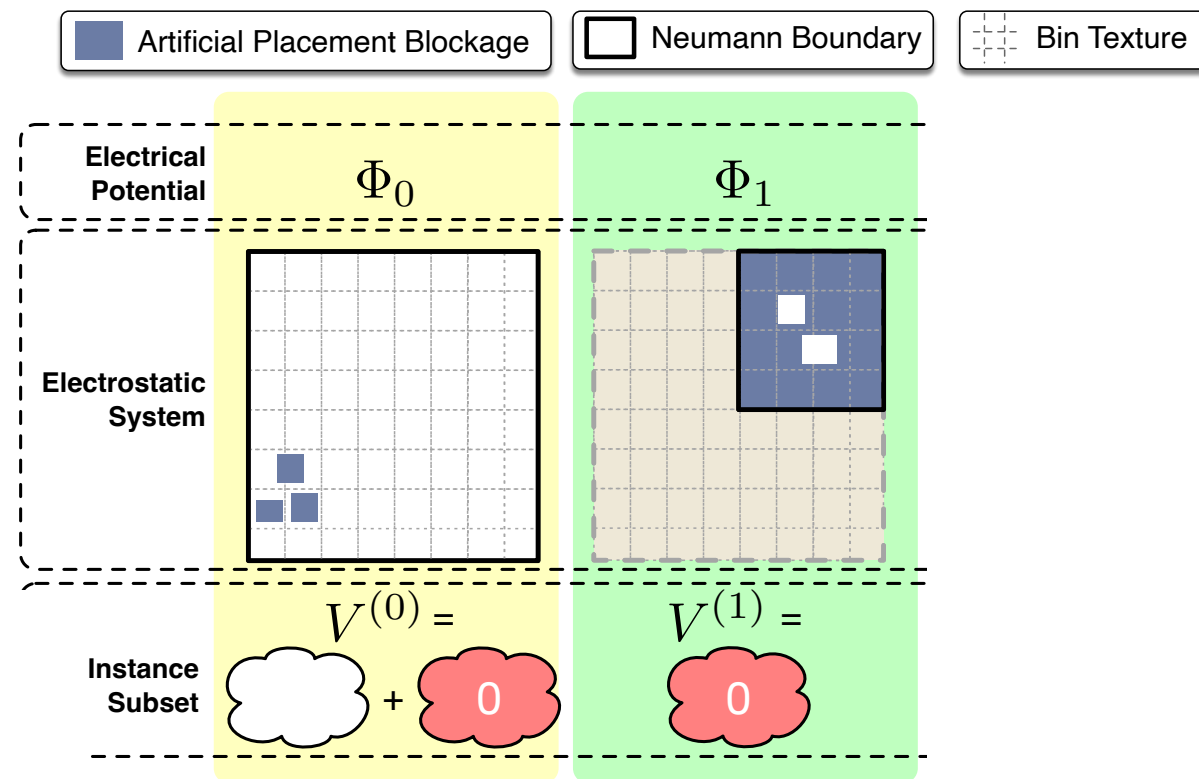
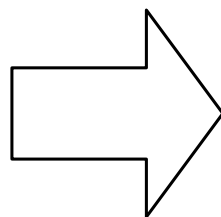
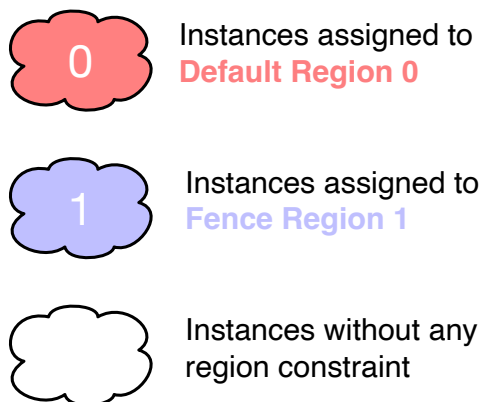
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Example

Region Locations



Instance Group

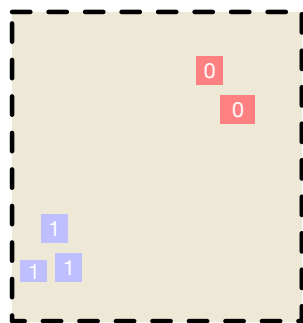


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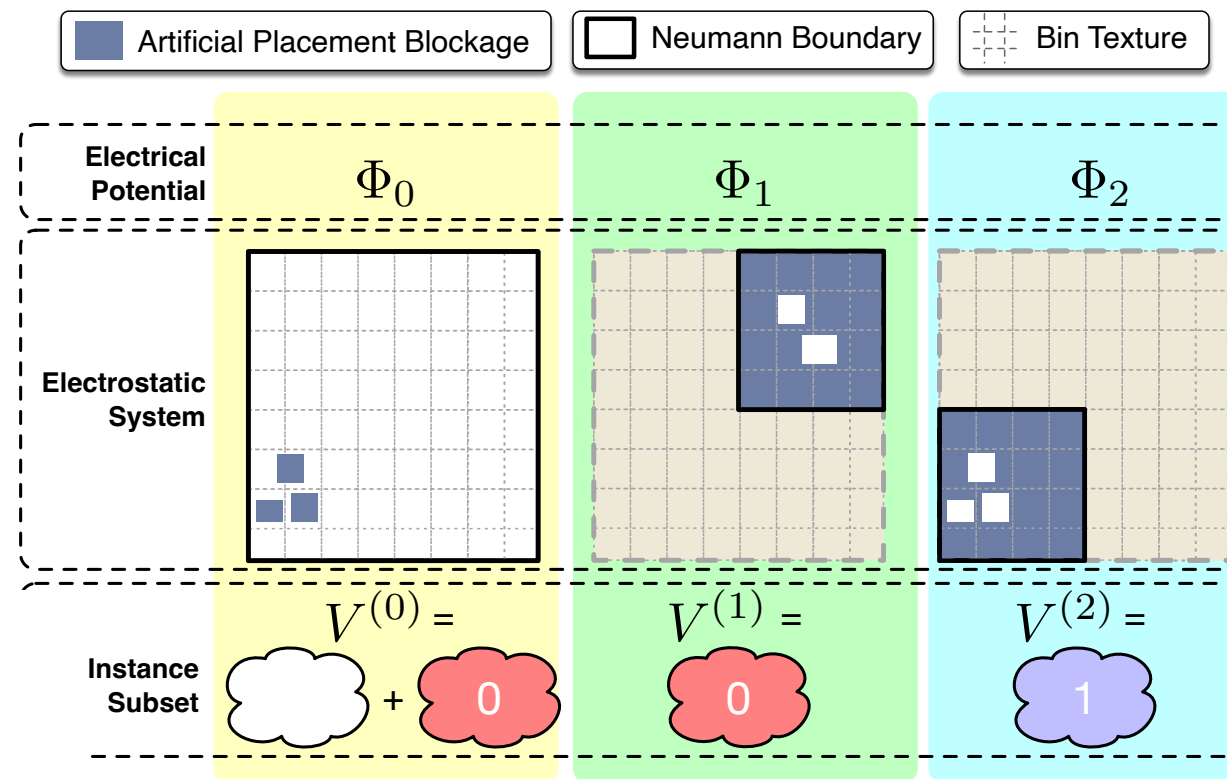
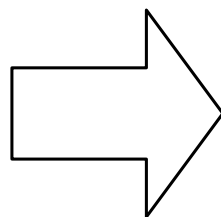
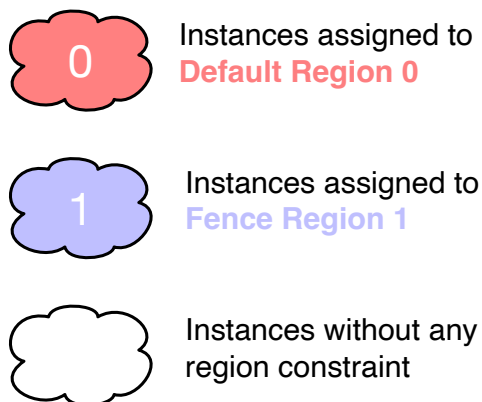
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Example

Region Locations



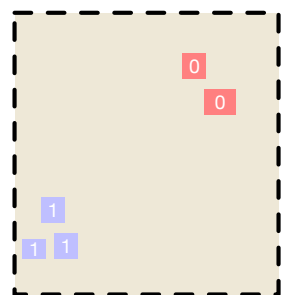
Instance Group



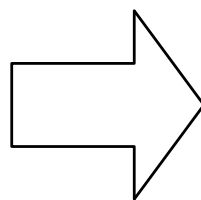
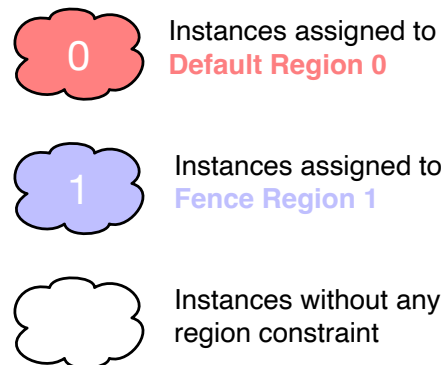
Binary-lifting-based region pruning algorithm

- ▶ Trim redundant areas away from the region by binary-lifting algorithm.
- ▶ Cells in each electrostatics system can only moved within the the trimmed **Neumann boundary**.
- ▶ Reduce memory complexity in proportion to the total area of the regions $O(\sum_i A_i)$. (**lower bound of complexity**)

Region Locations

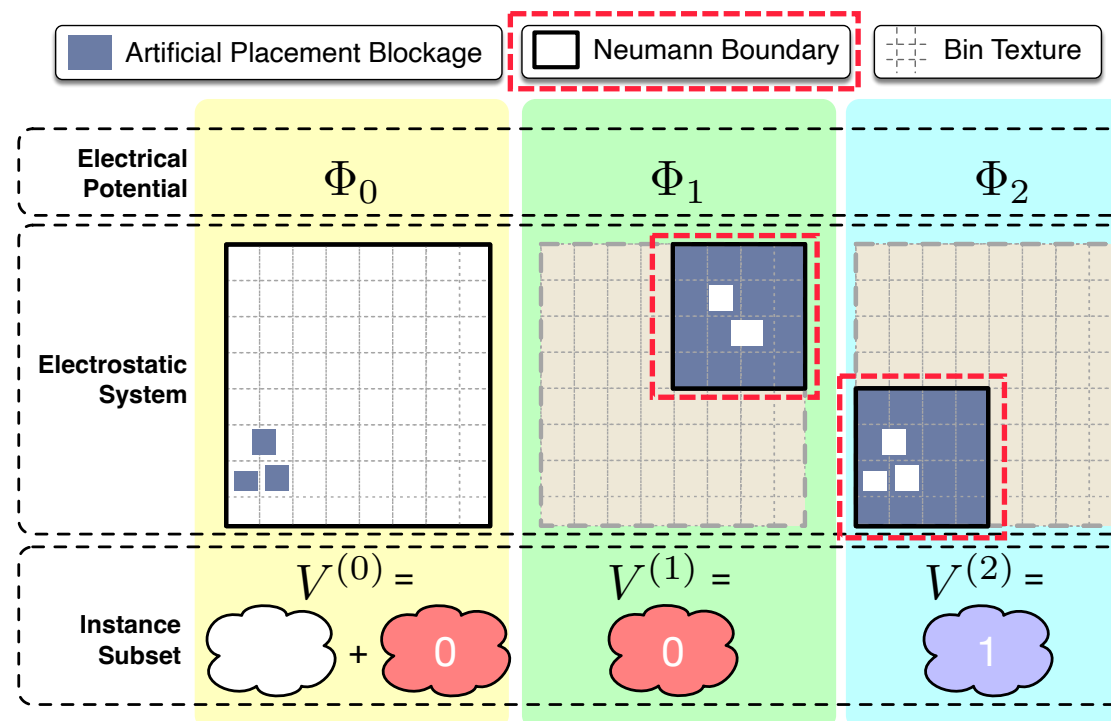


Instance Group



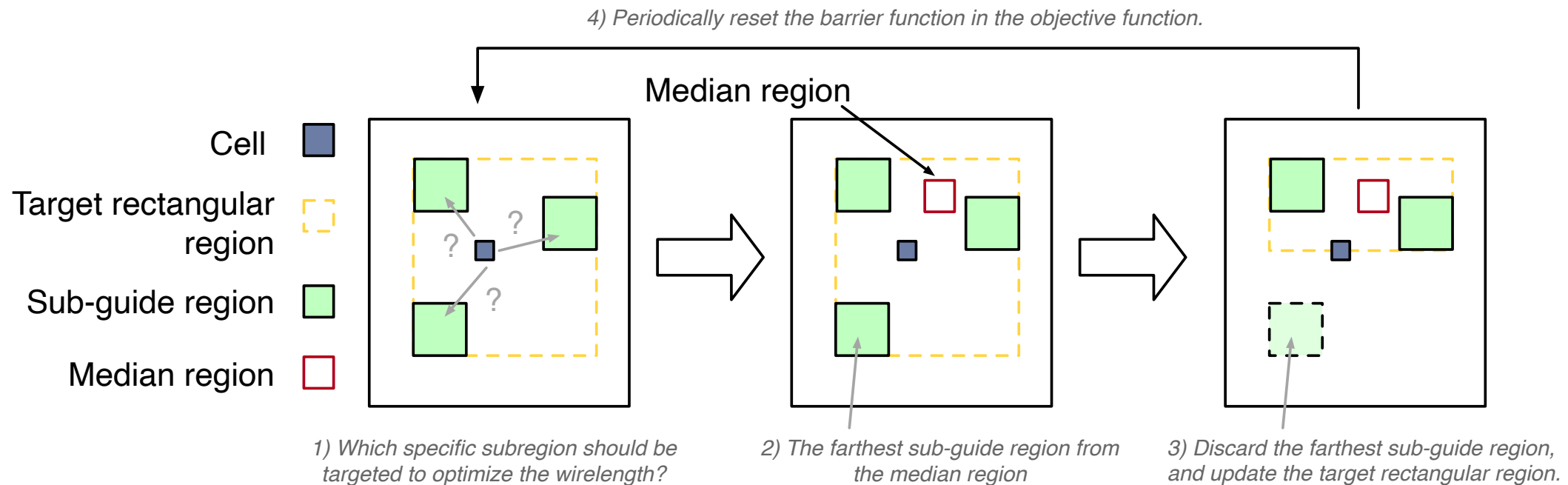
The example features one default region (red) and one fence region (purple).

Instances are divided into three instance groups based on their region constraints.



Tradeoff between wirelength and guide region constraints

- ▶ A barrier function to guide each cell to its **target rectangular region**.
- ▶ Target rectangular regions are updated periodically to discard the subregion that is farthest from **the median region** [Pan+, ICCAD'05]
 - ▶ i.e., the optimal region for each cell.



Analytical placement problems are transformed into unconstrained optimization problems:

$$\min_x f(x).$$

Gradient vector (first-order): $g^{(k)} = \nabla f(x^{(k)})$; Hessian matrix (second-order): $H^{(k)} = \nabla^2 f(x^{(k)})$

Target: approximate the inverse Hessian matrix in Newton's Method:

$$x^{(k+1)} = x^{(k)} - [H^{(k)}]^{-1} g^{(k)}$$

1. Define solution difference $s_{k-1} = x^{(k)} - x^{(k-1)}$ and gradient difference $y_{k-1} = g^{(k)} - g^{(k-1)}$,

$$y_{k-1} = \nabla^2 f(x^{(k)})s_{k-1} + \mathcal{O}(\|s_{k-1}\|^2).$$

2. Approximate the inverse Hessian matrix $T^{(k)} \approx [H^{(k)}]^{-1} = [\nabla^2 f(x^{(k)})]^{-1}$,

$$s_{k-1} = T^{(k)}y_{k-1}.$$

3. Leverage the the recursive property of $T^{(k)}$ and truncate after m iterations to reduce memory,

$$T^{(k)} \xleftarrow{\text{derive from}} T^{(k-1)} \leftarrow \dots \leftarrow T^{(k-m)} = [H^{(k-m)}]^{-1} \approx \frac{y_{k-1}^T s_{k-1}}{y_{k-1}^T y_{k-1}} I.$$

A Modified Nesterov's Accelerated LBFGS Algorithm

- Combine Nesterov's acceleration technique with LBFGS to speedup convergence.

- Divergence-aware preconditioner to mitigate gradient deviation.

- \mathcal{L} : Augmented Lagrangian function.

$$\min_{\mathbf{x}, \mathbf{y}} \mathcal{L}(\mathbf{x}, \mathbf{y}) = \tilde{W}(\mathbf{x}, \mathbf{y}) + \sum_{k=0}^{K_1-1} \lambda_k \mathcal{D}_k + \sum_{k=K_1}^{K_1+K_2-1} \eta_k \Gamma_k(\mathbf{x}^{(k)}, \mathbf{y}^{(k)}),$$

- $\mathcal{P} \in \mathbb{R}^{2 \times [N]}$: Preconditioner for all electrostatics systems.

$$\begin{aligned} \mathcal{P}_{0,i} &= \max \left\{ 1, \left[\frac{\partial^2 \mathcal{L}}{\partial x_i^2} \right]^{-1} \right\} \\ &= \max \left\{ 1, \left[\frac{\partial^2 \tilde{W}}{\partial x_i^2} + \sum_{k=0}^{K_1-1} \lambda_k \frac{\partial^2 \mathcal{D}_k}{\partial x_i^2} + \sum_{k=K_1}^{K_1+K_2-1} \eta_k \frac{\partial^2 \Gamma_k}{\partial x_i^2} \right]^{-1} \right\} \\ &= \max \left\{ 1, \left[\#pins(v_i) + \tau \sum_{k=0}^{K_1-1} \lambda_k \mathbb{I}_k(v_i) \text{area}(v_i) + \sum_{k=K_1}^{K_1+K_2-1} \eta_k \frac{\partial^2 \Gamma_k}{\partial x_i^2} \right]^{-1} \right\} \end{aligned}$$

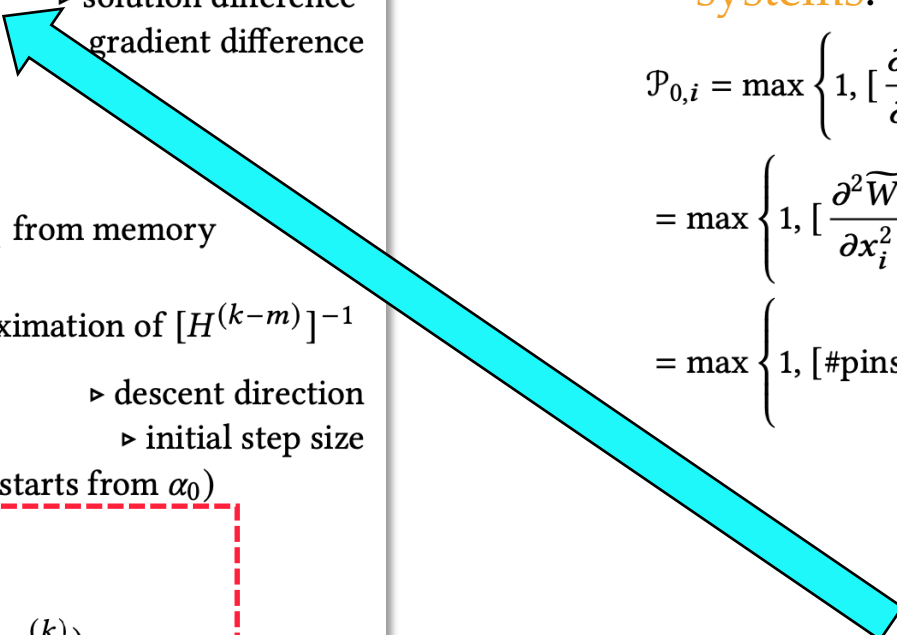


Preconditioned gradient

$$\nabla \hat{\mathcal{L}} = \nabla \mathcal{L} \odot \mathcal{P}$$

Algorithm 3 A Modified Nesterov's Accelerated LBFGS Algorithm

- 1: **Input:** major solution $u^{(k)}$, reference solution $v^{(k)}$, optimization parameter $a^{(k)}$, LBFGS memory length m .
- 2: **Output:** $u^{(k+1)}$, $v^{(k+1)}$, $a^{(k+1)}$.
- 3: $g^{(k)}, g^{(k-1)} \leftarrow \nabla f(v^{(k)}), \nabla f(v^{(k-1)})$
- 4: $s_{k-1} \leftarrow v^{(k)} - v^{(k-1)}$ ▷ solution difference
- 5: $y_{k-1} \leftarrow g^{(k)} - g^{(k-1)}$ ▷ gradient difference
- 6: $\rho_{k-1} \leftarrow \frac{1}{y_{k-1}^T s_{k-1}}$
- 7: store $s_{k-1}, y_{k-1}, \rho_{k-1}$
- 8: **if** $k > m$ **then**
- 9: remove $s_{k-m-1}, y_{k-m-1}, \rho_{k-m-1}$ from memory
- 10: **end if**
- 11: $\hat{T}_{k-m} \leftarrow \frac{y_{k-1}^T s_{k-1}}{y_{k-1}^T y_{k-1}} I$ ▷ approximation of $[H^{(k-m)}]^{-1}$
- 12: $d^{(k)} \leftarrow \text{LBFGS}(g^{(k)}, \hat{T}_{k-m})$ ▷ descent direction
- 13: $\alpha_0 \leftarrow 1$ ▷ initial step size
- 14: $\alpha^{(k+1)} \leftarrow \text{LINESEARCH}(v^{(k)}, d^{(k)}, \text{starts from } \alpha_0)$
- 15: $u^{(k+1)} \leftarrow v^{(k)} - \alpha^{(k)} d^{(k)}$
- 16: $a^{(k+1)} \leftarrow (1 + \sqrt{4a^{(k)} + 1}) / 2$
- 17: $v^{(k+1)} \leftarrow u^{(k+1)} + \frac{a^{(k+1)} - 1}{a^{(k+1)}} (u^{(k+1)} - u^{(k)})$
- 18: **return** $u^{(k+1)}, v^{(k+1)}, a^{(k+1)}$



Experimental Results

Machine

- ▶ Two Intel Xeon Platinum 8358 CPUs (2.60GHz, 32 cores) with 1024GB RAM
- ▶ One NVIDIA A800 GPU
- ▶ C++ with LibTorch for GPU acceleration

Benchmark Suites

- ▶ ISPD2015-FR: ISPD 2015 benchmark suite [Ismail+, ISPD'15] with fence regions only.
- ▶ ISPD2015-HR: Modified ISPD 2015 benchmark suite where some fence regions are modified into default regions and guide regions.

Placers for comparison

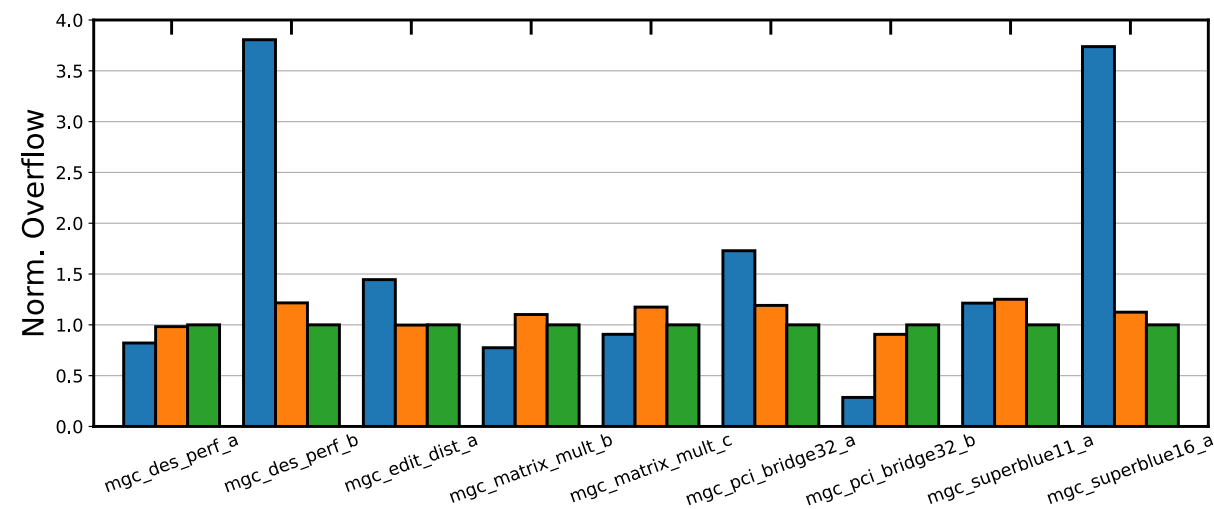
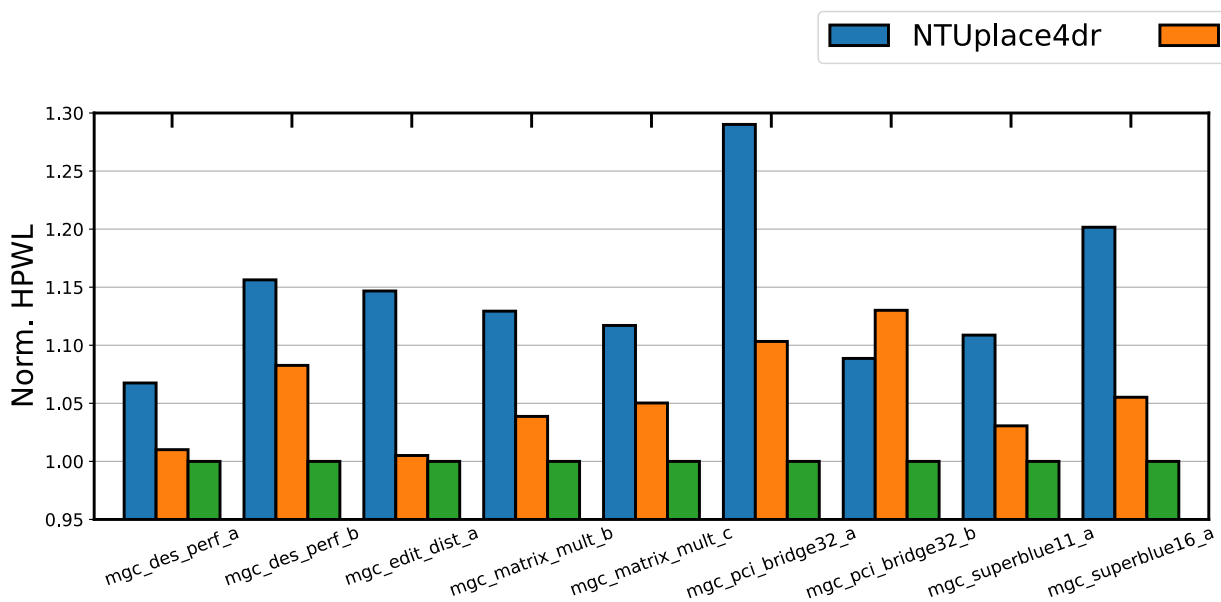
- ▶ NTUplace4dr [Huang+, TCAD'17]
- ▶ DREAMPlace 3.0 [Gu+, ICCAD'20]

Statistics of ISPD2015-FR benchmarks and its variant ISPD2015-HR.

Design	#Cells	#Nets	ISPD2015-FR	ISPD2015-HR		
			#Fence	#Fence	#Default	#Guide
mgc_des_perf_a	108K	115K	4	1	2	1
mgc_des_perf_b	113K	113K	12	4	4	4
mgc_edit_dist_a	127K	134K	1	0	0	1
mgc_matrix_mult_b	146K	152K	3	1	1	1
mgc_matrix_mult_c	146K	152K	3	1	1	1
mgc_pci_bridge32_a	30K	34K	4	1	2	1
mgc_pci_bridge32_b	29K	33K	3	1	1	1
mgc_superblue11_a	926K	936K	4	1	1	2
mgc_superblue16_a	680K	697K	2	0	2	0

HPWL and Global Routing Overflow Comparison on ISPD2015-FR

- ▶ **14.3%** better HPWL than NTUplace4dr
- ▶ **24%** smaller overflow than NTUplace4dr
- ▶ **5.6%** better HPWL than DREAMPlace 3.0
- ▶ **10%** smaller overflow than DREAMPlace 3.0



Consistently achieve better HPWL results than NTUplace4dr and DREAMPlace 3.0 across all cases!

Gradient Decent (GD)

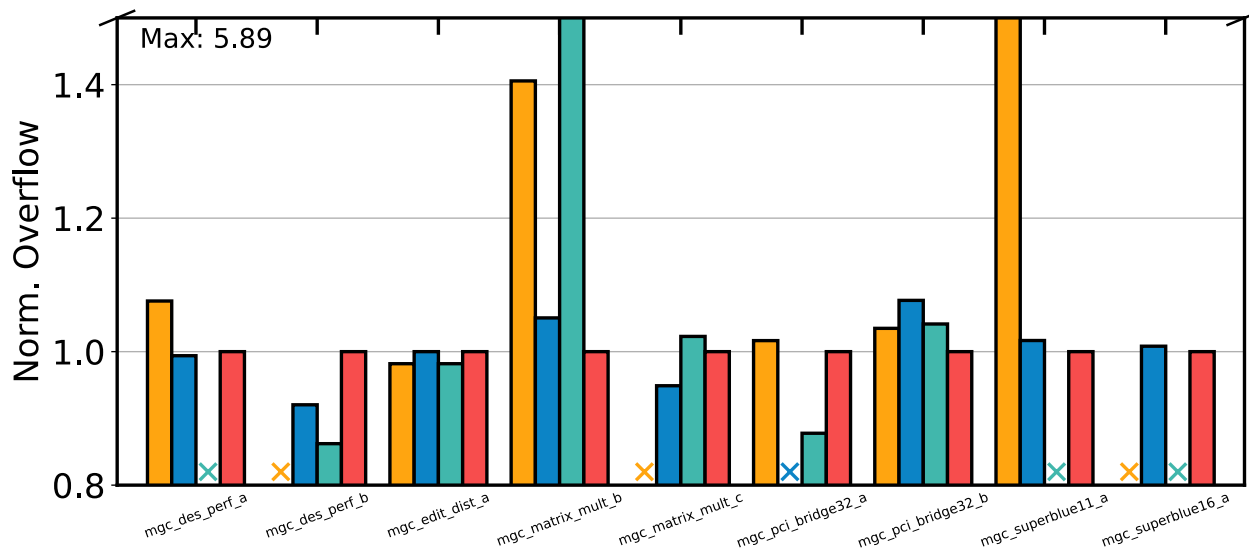
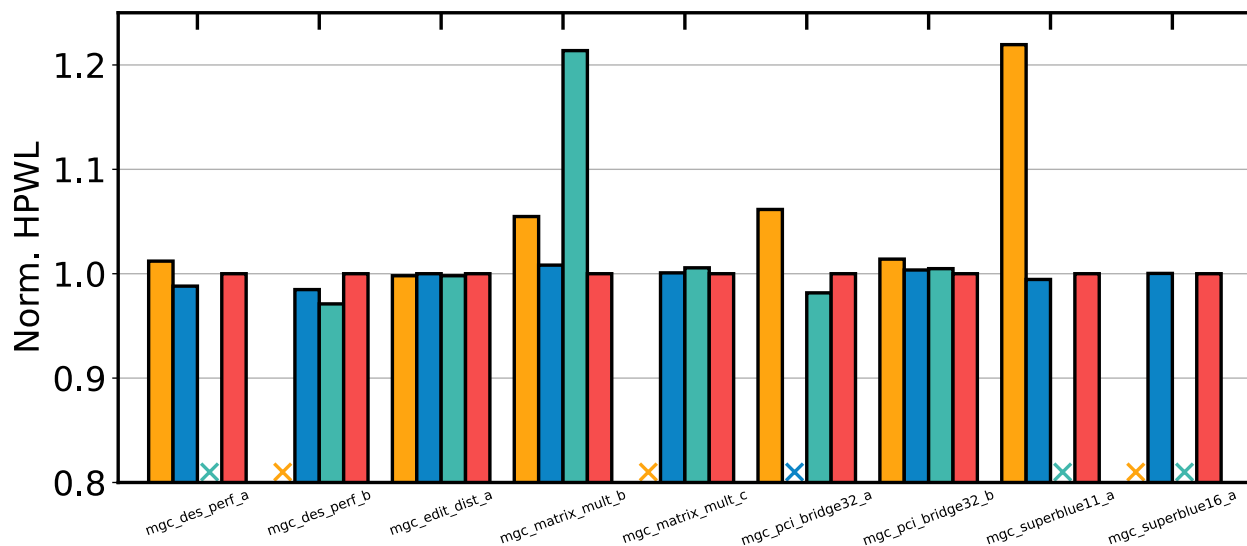
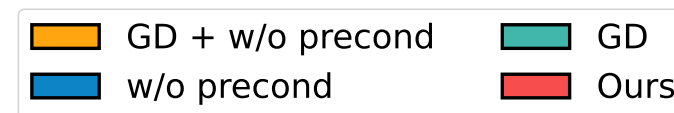
- ▶ 3/7 designs diverge
- ▶ +2.6% HPWL
- ▶ +12% Overflow
- ▶ -28% runtime

w/o precondition

- ▶ 1/7 design diverge
- ▶ -0.2% HPWL
- ▶ Almost the same overflow
- ▶ +24% runtime

GD + w/o precondition

- ▶ 3/7 designs diverge
- ▶ +32.7% HPWL
- ▶ +45% overflow
- ▶ -16% runtime



The Nesterov-accelerated LBFGS algorithm and preconditioner technique can significantly improve quality and robustness with minor runtime overhead.

Conclusion & Future Work

- ▶ We propose MORPH, an innovative ASIC placer specifically designed to manage **hybrid region constraints** (i.e., default regions, fence regions, and guide regions).
 - ▶ We propose a shared electrostatics model and a binary-lifting-based region pruning algorithm that integrate hybrid region constraints into a **unified** multi-electrostatic formulation.
 - ▶ We propose a wirelength-prioritized penalty method to manage the tradeoff between wirelength and guide constraint penalty.
 - ▶ Our proposed **Nesterov's accelerated LBFGS algorithm** can improve the quality and stability with second-order information.
- ▶ Experimental results demonstrate that we achieve a **5.6-14.3%** HPWL improvement and a **10-24%** overflow reduction compared to previous SOTA region-aware placers.

Future Work

- ▶ More efficient hybrid-region-aware legalization.

THANK YOU!

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Personal Website



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