TorchResist: Open-Source Differentiable Resist Simulator

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Introduction

Recent advancements in AI, including large language models and generative systems, have significantly increased computational demands, challenging Moore's law. Optical lithography, crucial for semiconductor manufacturing, faces high costs and photoresist modeling limitations. This paper introduces **TorchResist**, an **open-source**, **differentiable** photoresist simulator. TorchResist uses an **analytical**, **white-box** approach with fewer than twenty parameters, leveraging **GPU**-based differentiable programming for efficient co-optimization. Source code is available at https://github.com/ShiningSord/TorchResist.

Highlights

In TorchResist, we

1. Regularize the resist model using off-the-shelf analytical formulations
2. TorchResist is designed with fewer than twenty interpretable parameters
3. Calibrate the parameter with numerical methods on a calibration dataset
4. Utilize the parallel computing power of GPUs and achieve ∼90× acceleration.

TorchResist

Existing Formulation. The formulation of resist process has been well-established in previous works[2, 3, 4].

Problem. However, as lithography progresses to advanced, smaller nodes, strict analytical modeling of the resist process becomes increasingly difficult due to the intricate physical-chemical interactions at the nanometer scale and the growing complexity of production techniques.

Differentiable Programming and Numerical Method. Utilizing modern differentiable programming tools and harnessing the parallel computing power of GPUs, TorchResist significantly accelerates both calibration and inference processes.

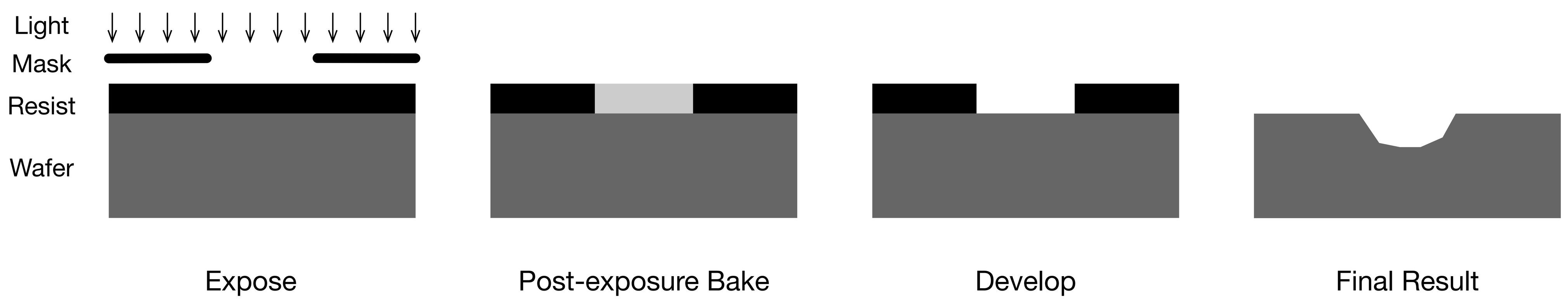

Figure 1. Illustration of a simplified positive resist process.

Calibration Dataset

We establish the calibration dataset with a commercial tool to adjust the parameters in TorchResist. Some examples from the calibration dataset is shown here.

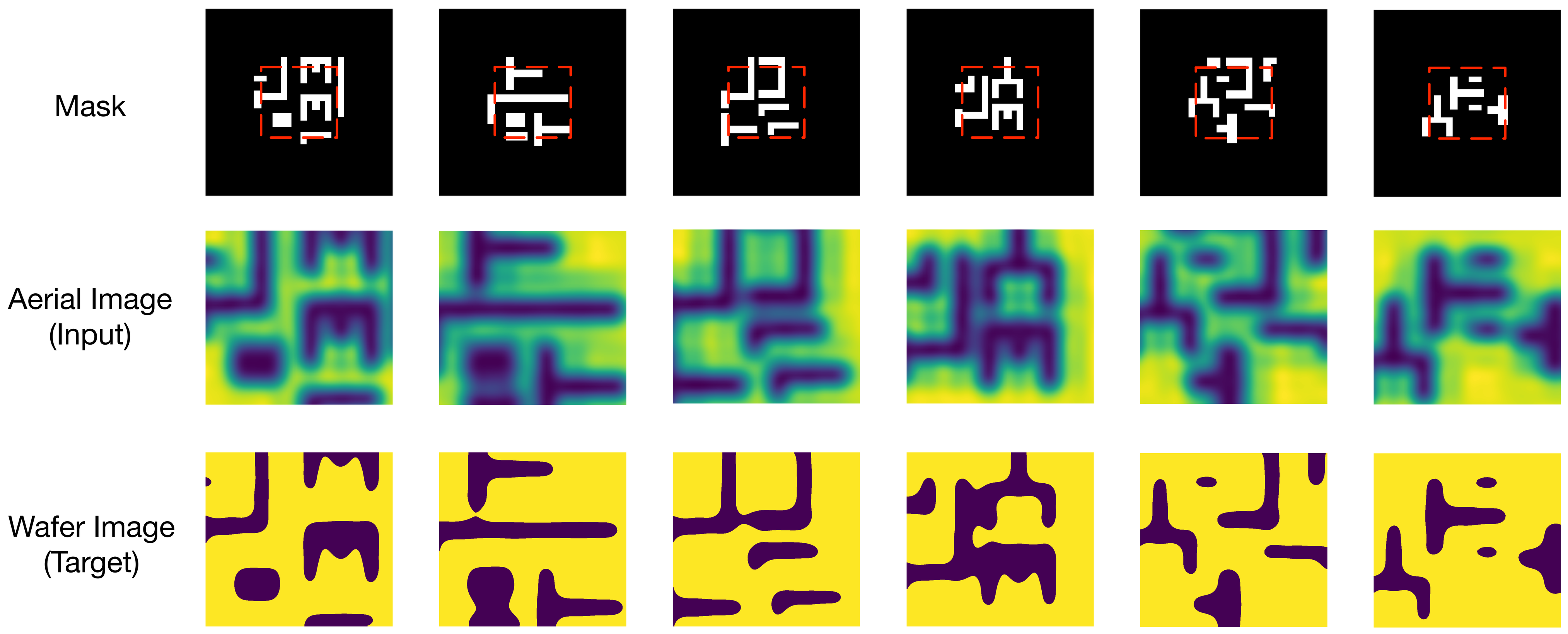

Figure 2. Illustration of the utilized dataset. The region of interest within the mask is highlighted by red dashed lines.

Evaluation on Accuracy

We get some parameters from domain knowledge and calibrate the remaining parameters in TorchResist with popular gradient descent method. The entire training process takes approximately 1 hour on a single NVIDIA A100 GPU. We illustrate the prediction of TorchResist in Fig. 3 and evaluate the performance with popular matrices in TABLE 1.

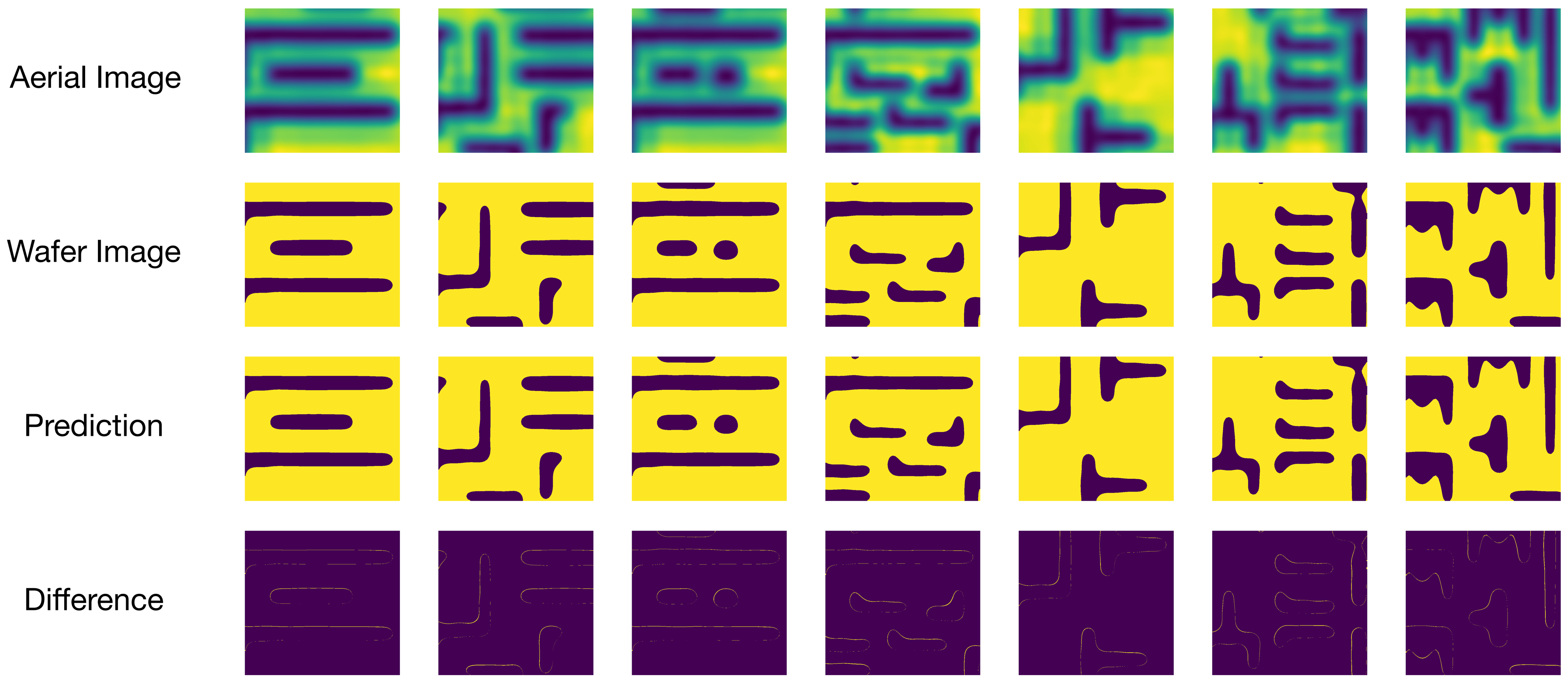

Figure 3. Illustration of the predictions of TorchResist. We also compare the predictions with groundtruth for the reference. The resolution of all the figures are 1 nm/pixel.

Table 1. The performance comparison of the resist model on LithoBench. The lithography model is a commercial tool.

Resist Model	Pixel Difference (%)	EPEMean (nm)	EPEmax (nm)	Differentiable	Depth Simulation
Fixed Thres.[1]	0.59	1.52	4.45	×	×
Variable Thres.[5]	0.49	1.21	3.95	×	×
TorchResist	0.22	0.73	2.87	✓	✓

Model Efficiency and Scale Robustness

We also evaluate the efficiency of TorchResist on a single NVIDIA 3090 GPU and report the average processing time for a single mask in TABLE 2. We also test the scale robustness of TorchResist in Fig. 4. The result shows the inference cost can be largely reduced without an obvious trade-off in precision.

Table 2. Comparison of model efficiency, measured by the average time required to process a 2µm × 2µm patch at different resolutions.

Resolution	Cost Time(s)	Ratio
1 nm/pixel	1.98	48.96
7 nm/pixel	0.04	1.00

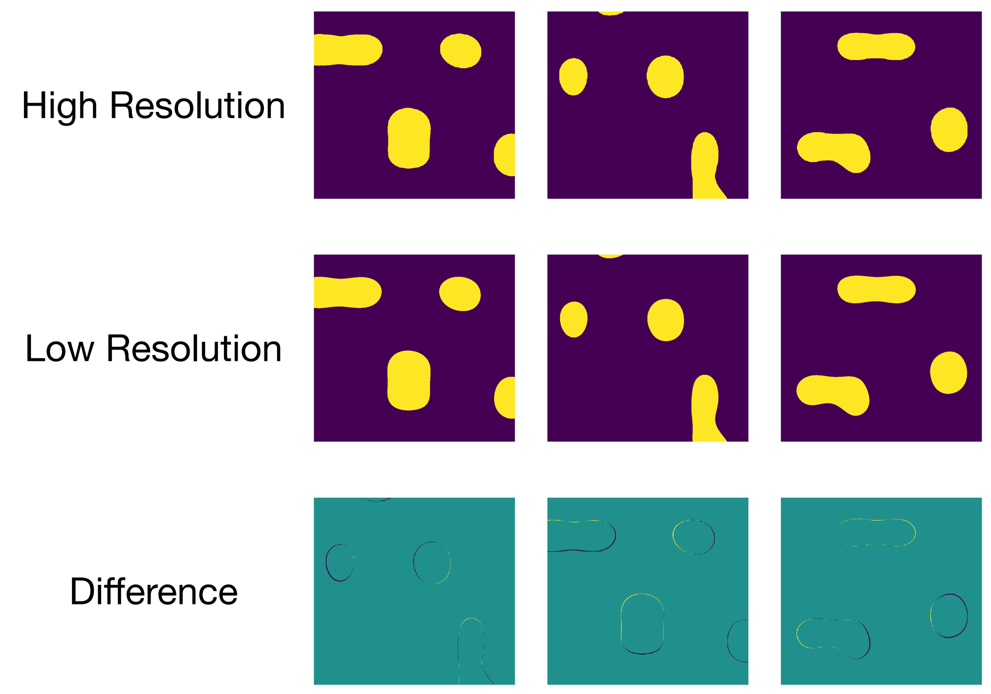

Figure 4. Comparison between results obtained at different resolutions.

References

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