

Practical Lithography Prediction System with AI Model

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Abstract

Computational lithography and recently proposed deep learning methods face several practical issues in real-world applications. We propose a system that implementing data collection, data alignment, training, and model evaluation that can be utilized in actual mask design procedure. On real mask images datasets, our method achieves 90.6% Mean Intersection over Union between predicted and real CD-SEM images with a speed of 2.5 ms per image. Our method demonstrates strong competitiveness.

Author Keywords

Lithography Prediction, Computational Lithography, Deep Learning, Mean IoU

1. Introduction

In the lithography process, light undergoes a diffraction effect while passing through a mask. After diffraction, the light is collected by a projection lens and focused onto the surface of the photoresist. This imaging process is an optical process. The light projected onto the photoresist triggers a photoelectrochemical reaction. Following baking, the photoresist partially dissolves in the developer solution, which is a chemical process. Figure 1 shows an example of a pair consisting of mask image (left) and its corresponding CD-SEM image (right) obtained after lithography. Lithography prediction, which involves predicting lithography effects for a specified mask image, is vital. It aids in understanding how to increase lithography resolution and process window, guides the optimization of lithography process parameters, reduces design and production costs, and improving product passing rate.

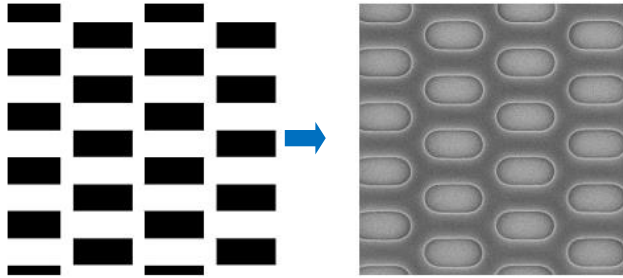


Figure 1. Illustration of lithography effect

Traditional lithography prediction mainly adopts the method of computational lithography, which simulates the optical and chemical processes in the lithography process based on physical and mathematical models. However, in practical applications, physical and mathematical models have many approximations and ideal assumptions, which differ from the actual situation and are difficult to be iteratively upgraded. Also, computational lithography methods face increasing time and computational costs, as well as prediction deviations of lithography effects compared to actual process conditions.

With the development of deep learning and artificial intelligence, they are also increasingly used in lithography prediction task. However, existing methods are mainly based on simulation data rather than actual lithography data. The problem of how to use

actual lithography data to achieve more accurate prediction has not yet been solved.

In response to the above issues, we propose a practical lithography prediction system. It is based on deep learning model and utilizes computer vision methods to achieve automatic data alignment. For evaluation of our method, we compare predicted images with real CD-SEM images and calculate their Mean Intersection over Union (IoU). Mean IoU of 90.6% shows that our method is very competitive.

2. Related Works

Computational lithography: Computational lithography is the use of mathematical, modeling, simulation, data analysis, and optimization techniques to predict and correct design issues, mask defects, manufacturing defects, and other challenges in the lithography manufacturing process before the wafer enters formal exposure. With the further advancement of technology, the models for computational lithography will become increasingly complex, requiring larger amount of computation resources and more CPUs for parallel computing, resulting in higher time and computational costs. Moreover, computational lithography often yields better results under ideal process conditions, while there is often a certain degree of deviation in predicting lithography effects under actual complex process conditions. [1-2] show recently progress in computational lithography.

Deep Learning: In recent years, machine learning methods including deep learning have achieved excellent results in many fields, and the field of lithography prediction is no exception. Relevant algorithms include [3-5]. These methods can deal with open source datasets. However, there are still many issues that need to be solved for real masks and CD-SEM images.

3. Proposed System

As shown in Figure 2, our proposed system consists of four modules: data acquisition, data alignment, training, and model evaluation.

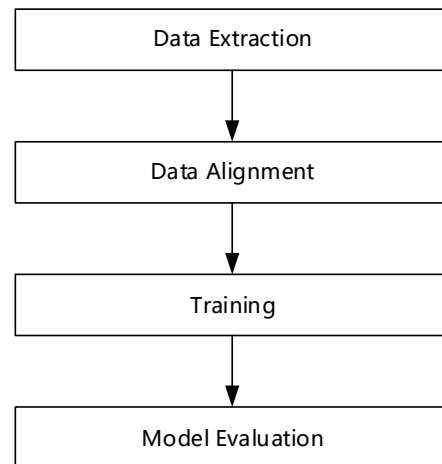


Figure 2. Proposed lithography prediction system

3.1 Data Extraction

Firstly, we design the mask. Then we make the mask and perform lithography and then we use an electron microscope to capture the effect after lithography. Totally we collect 1293 real CD-SEM images and recorded their approximate positions in the corresponding masks.

3.2 Data Alignment

Preparation work: Firstly, the physical resolution of the mask image and electron microscope image are normalized, as their corresponding physical dimensions are known. Based on this information, they can be normalized to the same physical resolution (the physical size corresponding to each pixel). Subsequent operations are performed on the normalized images.

For a mask image M , when taking its CD-SEM image, due to the accuracy limit of the control system, it is impossible to guarantee that the corresponding position of the CD-SEM image is completely overlap with M . In this case, there is a deviation between the CD-SEM image S and M . If using them directly as input and output in training, the noise caused by the deviation will affect the training effect. We introduce data alignment for it which can effectively remove the noise caused by this deviation.

According to S 's approximate corresponding positions saved in Section 3.1, a sub mask image M_{Enlarg} is extracted with a larger range than the CD-SEM image to ensure that M_{Enlarg} contains the accurate position M in the mask corresponding to S . The alignment task is to find the actual position of M in M_{Enlarg} . Let the width and height of M_{Enlarg} be W_{ME} , H_{ME} , and the width and height of S be W_s , H_s . Since physical resolution normalization has already been performed, it is obvious that $W_{ME} > W_s$, $H_{ME} > H_s$.

As shown in Figure 3, scanning M_{Enlarg} with S as sliding window from left to right and top to bottom is performed. Each offset (dx, dy) representing a candidate subimage $M_{dx, dy}$ for the accurate position M in M_{Enlarg} corresponding to S . For the current (dx, dy) , a similar score $T_{dx, dy}$ between $M_{dx, dy}$ and S is obtained based on computer vision technique. All possible (dx, dy) are enumerated, and the offset values (dx_M, dy_M) which correspond to the maximum $T_{dx, dy}$ are obtained as the accurate position M corresponding to S .

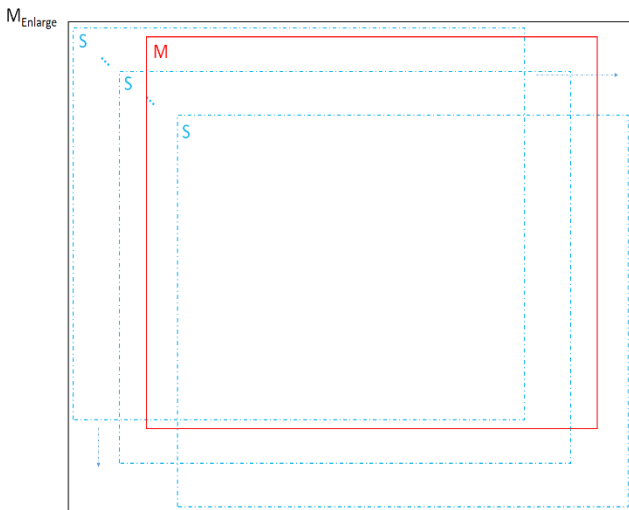


Figure 3. Scanning in M_{Enlarg} to find S 's corresponding position

3.3 Training

The extracted 1293 pairs of images are divided into training and test datasets. A generative network is designed to predict CD-SEM image of input mask image. The training process is shown in Figure 4 where the mask image is sent to the generative network as input and predicted image is obtained. Then the predicted image and real CD-SEM image are compared and the result is used to update the generative network.

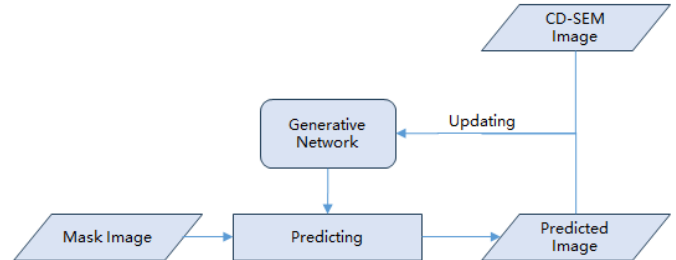


Figure 4. Training process

3.4 Model Evaluation

When training is finished, the Mean IoU of predicted images and their corresponding real CD-SEM images in test dataset are calculated to evaluate the model's accuracy. We use this evaluation criterion because it not only reflects the consistency between the predicted image and the CD-SEM image, but also is independent of the physical scale.

4. Experimental Result

We use a workstation with one NVIDIA RTX 3060 with 12G memory to verify our method. Experiments are performed on 1293 pair of images. According to evaluation method mentioned in Section 3.4, Mean IoU is 90.6% for test dataset. The predicting speed is 2.5ms per image. Figure 5 gives an example of test result. The predicted image seems identical to the real CD-SEM image. It is a very competitive result showing that our method is highly effective to real lithography prediction application scenario.

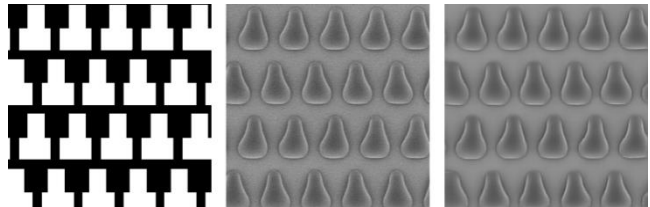


Figure 5. An example of test result. Left side is the mask image. Its corresponding CD-SEM image is in the middle. And right column is the predicted image.

5. Conclusion

In response to the limited practicality of existing mask lithography prediction methods, we propose a system that incorporates computer vision-based auto-alignment and deep learning model based mask lithography prediction. This system achieves a 90.6% accuracy and 2.5 ms per image processing speed on real datasets, meeting the accuracy requirements of the design. It holds substantial significance for the application of AI in lithography prediction tasks.

6. References

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