A Fragment-based Pattern Prediction Method for Accelerating Large-Scale Mask Simulation

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As process nodes continue to shrink, the linewidth of masks decrease accordingly, which significantly increases the data volume required for mask simulation[1]. Therefore, when performing pattern prediction (PP) on large and complex mask geometries, conventional (conv) PP methods still struggle to overcome the substantial computational cost and the resulting efficiency bottlenecks. As shown in Fig. 1(a), conv PP methods typically rely on a FFT-based workflow: the target pattern and the PSF are first zero-padded, followed by 2D FFT, pixel-wise multiplication in the frequency domain, and inverse FFT to obtain the energy image. However, as illustrated in Fig. 1(b), the conv FFT-based approach requires computing all pixels simultaneously, leading to substantial computational overhead. Its computational cost increases exponentially with pattern size, making PP for large-scale layouts extremely time-consuming. To address this issue, we propose a fragment-based (FB) PP method that reduces computational complexity by dividing the target pattern into smaller sub-patterns. As shown in Fig. 1(c), each sub-pattern is individually processed by PP using a smaller post-zero-padding PSF, and the resulting sub-energy images are subsequently assembled to form the final energy image. Fig. 1(d) shows the time complexity of the conv FFT method and the proposed FB method. Fig. 2(a) shows the proposed FB algorithm. As illustrated in Fig. 2(b), although the proposed FB method can reduce computation time, dividing the pattern into multiple sub-patterns brings repeated computation regions. Consequently, when the pattern size is small, its runtime may even exceed that of the conv FFT-based method. To evaluate the practical effectiveness of the proposed approach, we fixed the PSF size and gradually increased the target pattern size to analyze how the time complexity of the proposed FB method varies with the fragment factor k relative to the conv FFT method, where k denotes that each side of the pattern is divided into k parts, resulting in a total of k^2 fragments. As shown in Fig. 3(a), the proposed method begins to reduce computation time only when the target pattern becomes sufficiently large, as indicated by the green highlighted. In our simulation, we (1) used a double-Gaussian PSF to model 50 keV electron scattering in a full EUV binary mask with a 64 nm HSQ resist layer, and (2) compared fidelity and runtime for a 6T-SRAM poly layer [Fig. 3(b)] and a curvilinear via layer [Fig. 3(c)] under a zero-width beam and 1 nm grid size. According to the simulation results in Table I, repeating the two target patterns to form matrices of different sizes show that both EPE_{mean} and NMSE remain extremely low across all pattern dimensions and k values. For the runtime comparison, we evaluated different k values using a 100,000×50,000 pattern dimension, as shown on the right side of Table I. The results show that the speed-up of the proposed method over the conv method increases as k increases, achieving the maximum improvement of 42% when k=6. In conclusion, the proposed FB method optimizes the PP process for large pattern dimensions, effectively reducing runtime while maintaining pattern accuracy.

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[1] W. Yao et al., *IEEE Trans. Comput.-Aided Design Integr. Circuits Syst.*, **42**, 1 (2023).

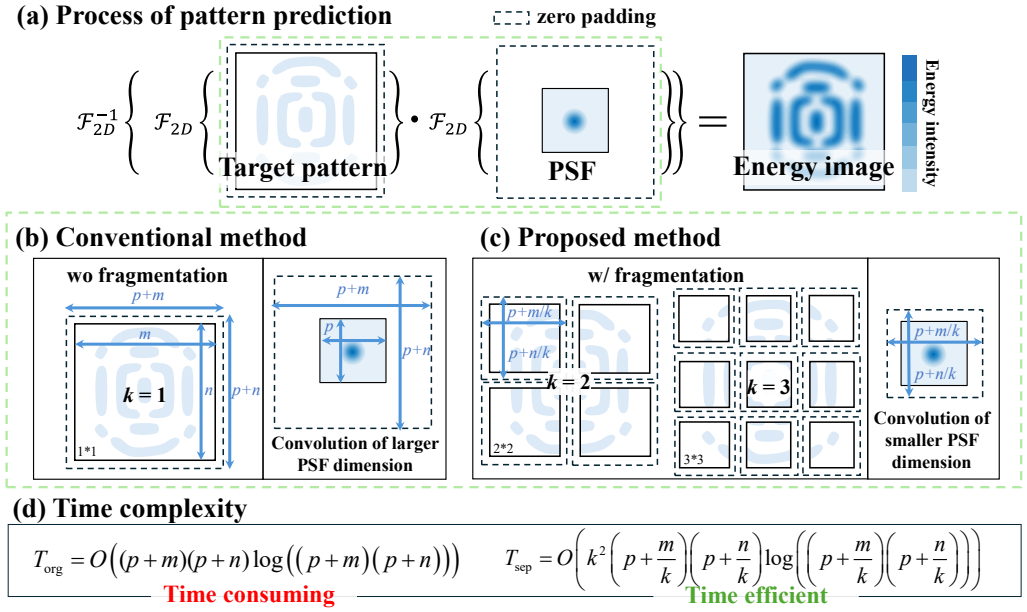

Fig. 1 illustrates (a) the process of pattern prediction method, (b) the convolution region size and time complexity of the conventional FFT-based method for the target pattern and the PSF, (c) the proposed fragment-based method showing its convolution region size and (d) time complexity of two methods.

Input: Target pattern
Output: Energy image
1: **if** $T_{sep}(m,n,p,k) < T_{org}(m,n,p)$ **do**
2: Fragment the target pattern into k^2 sub-patterns
3: Zero-pad each sub-pattern and PSF to equal size
4: Convolve each sub-pattern with the PSF
5: **else**
6: Zero-pad the target pattern and PSF to equal size
7: Convolve target pattern with the PSF
8: **end**

(a)

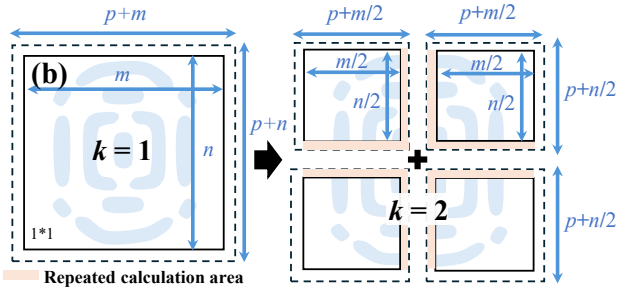

Fig. 2 illustrates (a) the algorithm and (b) the repeat computation regions when using the proposed fragment-based method.

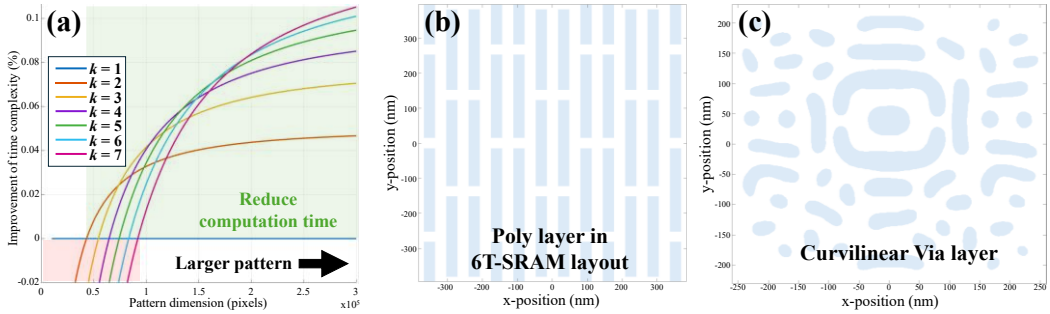

Fig. 3 illustrates (a) the improvement in time complexity achieved by the proposed fragment-based method compared with the conventional FFT-based method, as the value of fragment factor k (the number of fragments per pattern side) is adjusted under a fixed PSF size while scaling up the target pattern size. Two different patterns used as test patterns: (b) a 6T-SRAM poly layer and (c) a curvilinear via layer.

Table I numerical comparison of fidelity and runtime between the conventional FFT-based method and the proposed fragment-based method under various values of k.

Fidelity			Efficiency			
Poly / CL Via	Fidelity index	Proposed fragment-based	Pattern dimension (100,000*50,000)	Conventional FFT-based	Proposed fragment-based	improvement
100,000*50,000 (k = 2)	EPE_{mean}	0 nm / 0 nm	k = 1	175.49 sec	—	—
	NMSE	8.0×10^{-14} % / 8.9×10^{-14} %	k = 2	—	149.78 sec	14.65%
120,000*60,000 (k = 3)	EPE_{mean}	0 nm / 0 nm	k = 3	—	130.84 sec	25.44%
	NMSE	7.6×10^{-14} % / 7.7×10^{-14} %	k = 4	—	119.13 sec	32.12%
130,000*70,000 (k = 4)	EPE_{mean}	0 nm / 0 nm	k = 5	—	104.41 sec	40.50%
	NMSE	2.8×10^{-13} % / 2.8×10^{-13} %	k = 6	—	102.63 sec	41.52%
		Extreme low error				Significantly improved