Fast aerial image simulations using one basis mask pattern for optical proximity correction

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Aerial image simulation is one of the key parts in the model-based optical proximity correction (OPC) technique, which has become a must have process to improve lithography performance with ever-decreasing feature sizes. In this paper, a fast aerial image simulation approach is proposed by using one basis mask pattern to generate a lookup table, where the convolutions of the basis pattern with the partially coherent kernels are precalculated and stored. A rectilinear polygon mask pattern used in integrated circuit layouts can be decomposed into several shifted basis patterns. Its convolutions with kernels for use in aerial image calculation can then be quickly obtained from the precalculated lookup table by applying the translation-invariant property of two-dimensional convolution. Simulations conducted by using the proposed approach have demonstrated that this approach yields a superior quality in the fields of aerial image calculation and OPC optimization, due to the advantage of dramatically decreasing the storage requirement. It is fully expected that this approach will be simple to implement and will provide a useful practical means for OPC systems. © *2011 American Vacuum Society*. [DOI: 10.1116/1.3659718]

I. INTRODUCTION

With ever-decreasing feature size, attempts at pushing the limit of optical lithography have made the optical proximity correction (OPC) technique a must have process as part of the resolution enhancement techniques to improve the performance of lithography.[1–3] The model-based OPC can be roughly classified into polygon-based OPC and pixel-based OPC. These two categories differ mainly in their treatments of mask geometries as polygons or as pixel-based images. Since the pixel-based OPC techniques have the advantage of more flexibility in mask changes when optimizing the target pattern, they have been gaining increasing research interest in recent years. Poonawala and Milanfar introduced the steepest descent algorithm for the optimization framework to significantly reduce the computation complexity.[3] Ma and Arce further generalized this algorithm for phase shifting masks and partially coherent imaging systems, which are widely used in current lithographic tools.[4–6] Chan *et al*.[7] and Shen *et al*.[8] introduced the level-set-based algorithm to ameliorate the manufacturability of the optimized masks. Shen *et al*. also took defocus and aberration into consideration to enhance the robustness of the layout patterns.[9] Yu and Yu investigated the impact of various objective functions and their superposition for inverse lithography patterning, and proved that a clever mix of the objective functions can improve the resolution limits while maintaining manufacturing-friendly masks.[10] However, the flexibility of pixel-based OPC usually results in a more complex pattern, and thus makes the mask more difficult to manufacture.[11] The polygon-based OPC, in which the edge of the mask pattern is moved to compensate for the error of image intensity, is still the dominant OPC methodology in industry.

Generally, the process of model-based OPC includes the forward modeling known as lithography simulation and the inverse process, which aims to optimize the mask layout. Since it is usually necessary to repeat the forward modeling process a number of times in the inverse optimization, fast aerial image simulation algorithms are highly desirable for practical OPC systems. According to Hopkins' theory,[12–14] the imaging process of typical lithographic tools can be modeled as a partially coherent system, and the aerial image can be calculated by an equation with a fourfold integration, which is extremely time-consuming in direct computation. There are various methods used to simplify the integration for aerial image simulation, such as the analytical method,[15–17] the pupil shift matrix method,[18] and the cross triple correlation method.[19,20] The theory of sum of coherent systems[21,22] or optical coherent approximation[23] has been introduced in OPC due to its capability of approximating a partially coherent imaging system with the superimposition of several coherent systems, or kernels; thus, the integration can be avoided and the speed of aerial image simulations is greatly improved. This method is particularly suitable for polygon-based OPC, as the convolutions of a mask pattern with kernels can be precalculated and saved as a lookup table, which in turn can further speed up the aerial image simulation.

Cobb and Zakhor did pioneering work on the lookup table method, in which the mask pattern was decomposed into the sum of several primitive trapezoids according to their contributions.[21,22] Then the trapezoids were divided into finitely supported "upper right corner rectangles," whose convolutions

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with the kernels were precalculated and saved as a lookup table. However, just as Pati *et al.* pointed out,[24] since finitely supported rectangles were used in this approach, each resizing of the rectangle had to be handled individually. This means that a large number of upper right corner rectangles had to be used to generate the lookup table. To overcome this drawback, Pati *et al.* exploited the structure inherent in mask patterns and defined a set of building blocks to construct the mask patterns.[24] These building blocks are two-dimensional (2D) functions, and each of them is actually a step function in one direction with a finite width in the other direction. As the step function is infinitely supported, the translation-invariant property of convolution can be applied, and only convolutions of each step function with kernels need to be saved in the lookup table. In this way, according to their report, for a mask area of $M \times M$ discrete grid points, only M infinitely supported step functions were required to generate the lookup table. In contrast to the $M \times M$ upper right corner rectangles that had to be used in Cobb and Zakhor's method, Pati *et al.*[24] claimed to have achieved an order of magnitude reduction in storage. Even so, the number of step functions used in this approach is still too large. Recently, Yu *et al.* reported a vertex-based convolution method for lookup table generation,[25] in which any rectilinear polygon mask pattern was represented as a combination of several vertices, and any rectilinear polygon convolution was decomposed into the summation of the convolutions of the regions to the upper right of each vertex. However, as the lookup table for each kernel was generated from the convolutions of all the right upper rectangles within the support region, this method still required a huge amount of storage capacity.

In this paper, we propose an approach for lookup table generation by using only one basis mask pattern. This basis pattern is a 2D step function that is fully and only characterized by a vertex. It looks like an upper right rectangle, but it is actually infinitely supported. Similar to the vertex-based convolution method, we can decompose any rectilinear polygon into several shifted basis patterns. However, having noticed that this basis pattern is infinitely supported, we can thus exploit the translation-invariant property of 2D convolution. Consequently, we have demonstrated that it only needs to store the convolution of the basis pattern with each kernel in the lookup table, so the storage requirement is greatly reduced. We have performed simulations of aerial image calculation and OPC optimization to verify the feasibility and efficiency of the proposed approach.

II. THEORY

The imaging process in optical lithography can be modeled as a pupil function with a partially coherent illumination source, namely the partially coherent system, as shown in Fig. 1. According to Hopkins' theory,[12–14] the intensity $I(x, y)$ in the image plane can be expressed as

$$I(x,y) = \iint \iint M(x_1,y_1)\mathrm{TCC}(x-x_1,y-y_1;x-x_2,y-y_2) M^*(x_2,y_2)dx_1dx_2dy_1dy_2, \quad (1)$$

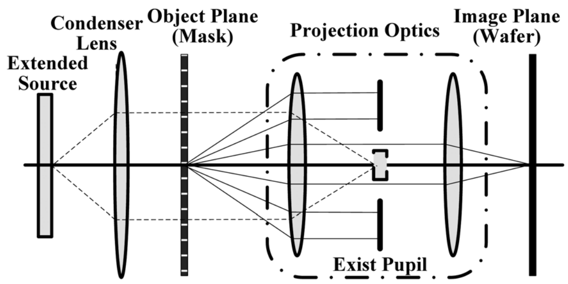

FIG. 1. Optical imaging system in lithography tools.

where $M(x, y)$ is the mask pattern, $M^*(x, y)$ is its complex conjugate, and TCC is the transmission cross coefficient in the spatial domain defined as

$$\mathrm{TCC}(x_1,y_1;x_2,y_2) = J(x_1-x_2,y_1-y_2)P(x_1,y_1) P^*(x_2,y_2). \quad (2)$$

Here, $J(x_1-x_2, y_1-y_2)$ is the mutual intensity that describes the coherence of the illumination source, $P(x, y)$ is the point spread function that fully characterizes the property of the projection lens, and $P^*(x, y)$ is its complex conjugate.

Since the TCC matrix is Hermitian and positive definite, it can be decomposed into a series of positive eigenvalues with corresponding eigenvectors, which are also called partially coherent kernels:

$$\mathrm{TCC}(x_1,y_1;x_2,y_2) = \sum \lambda_n \varphi_n(x_1,y_1)\varphi_n^*(x_2,y_2), \quad (3)$$

where λ_i is the ith eigenvalue corresponding to the ith eigenfunction $\varphi_i(x, y)$. By ordering all the eigenvalues in magnitude in a descending manner, it can be found that the ordered eigenvalues decay rapidly; thus, the truncation of the summation in Eq. (3) will be a good approximation. Consequently, the aerial image can be achieved by using only several eigenvectors as[22]

$$I(x,y) = \sum_{n=1}^{N} \lambda_n |\varphi_n(x,y) \otimes M(x,y)|^2, \quad (4)$$

where $\otimes$ denotes 2D convolution and N is the number of truncated eigenvectors. In this way, the aerial image of partially coherent systems is approximated as the superimposition of several coherent systems, or kernels; thus, the fourfold integration in Eq. (1) is avoided and the computation complexity is reduced.

Although Eq. (4) significantly simplifies the aerial image calculation in partially coherent systems, the 2D convolutions involved are still quite time-consuming. To overcome this drawback and to further speed up the calculation, several lookup table methods have been previously introduced.[21,22,24,25] However, many basis mask patterns have to be used in these methods, and their convolutions with kernels have to be stored to generate the lookup table, which usually results in unreasonable storage requirements. Here, we present a new approach to generate the lookup table by using only one basis mask pattern.

As shown in Fig. 2, the basis mask pattern, or briefly the basis pattern, is a 2D step function that looks like an upper right rectangle, but it is actually infinitely supported in both directions:

$$U_0(x,y) = \begin{cases} 1, & x \geq 0, y \geq 0 \\ 0, & \text{otherwise} \end{cases}. \tag{5}$$

We define a shifted basis pattern as the shifting of the basis pattern in the plane:

$$U_k(x,y) = U_0(x - x_k, y - y_k) = \begin{cases} 1, & x \geq x_k, y \geq y_k \\ 0, & \text{otherwise} \end{cases}, \tag{6}$$

where (x_k, y_k) represent the coordinates of the vertex P_k of the shifted basis pattern. It is obvious that any shifted basis pattern can be characterized fully and only by its vertex coordinates. For example, the basis pattern is characterized by the vertex at the origin (0, 0).

By such definitions, as shown in Fig. 2, any rectilinear polygon mask pattern can be decomposed into the sum of several shifted basis patterns:

$$M(x,y) = \sum_{k=1}^{K} \mu_k U_k(x,y), \tag{7}$$

where U_k is the shifted basis pattern at vertex P_k with coordinates of (x_k, y_k), μ_k is the contribution of U_k with a value being 1 or -1, and K is the total number of shifted basis patterns that are used to form the mask pattern. By substituting Eq. (7) into Eq. (4), and noticing the linear property, the aerial image of any mask pattern can be represented as

$$\begin{aligned} I(x,y) &= \sum_{n=1}^{N} \lambda_n \left| \varphi_n(x,y) \otimes \sum_{k=1}^{K} \mu_k U_k(x,y) \right|^2 \\ &= \sum_{n=1}^{N} \lambda_n \left| \mu_k \sum_{k=1}^{K} \varphi_n(x,y) \otimes U_k(x,y) \right|^2. \end{aligned} \tag{8}$$

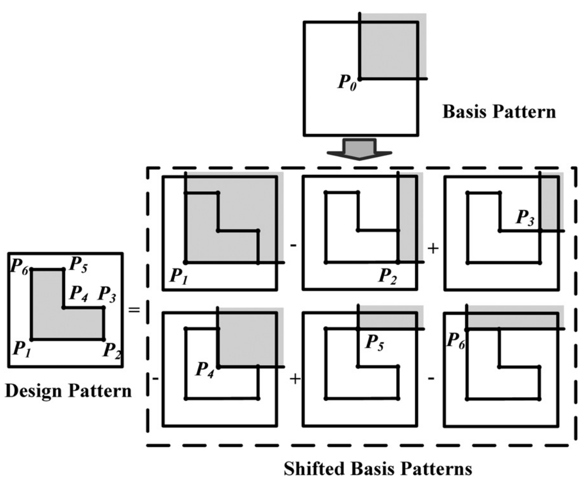

FIG. 2. Decomposition of any rectilinear polygon mask pattern into the sum of several shifted basis patterns according to their contributions.

Substituting Eq. (6) and applying the translation-invariant property of convolution, we get

$$\begin{aligned} I(x,y) &= \sum_{n=1}^{N} \lambda_n \left| \mu_k \sum_{k=1}^{K} \varphi_n(x,y) \otimes U_0(x - x_k, y - y_k) \right|^2 \\ &= \sum_{n=1}^{N} \lambda_n \left| \mu_k \sum_{k=1}^{K} (\varphi_n \otimes U_0)(x - x_k, y - y_k) \right|^2 \\ &= \sum_{n=1}^{N} \lambda_n \left| \mu_k \sum_{k=1}^{K} E_{n0}(x - x_k, y - y_k) \right|^2, \end{aligned} \tag{9}$$

where the convolution of the nth kernel with the basis pattern is denoted as

$$E_{n0}(x,y) = (\varphi_n \otimes U_0)(x,y). \tag{10}$$

The derivation of Eq. (9) means that with the help of the basis pattern, we only need to save E_{n0} ($n = 1, 2, ..., N$) to generate the lookup table.

Since only one basis mask pattern is needed to generate the lookup table, the approach proposed here only requires storage of $O(1)$, which is quite low and acceptable for most current computers. As the convolutions of all the upper right rectangles with kernels are needed to be stored using Cobb and Zakhor's method for a mask area of $M \times M$ discrete grid points, the storage requirement is $O(M^2)$, which corresponds to the number of possible upper right rectangles in the area. In the method of Pati *et al.*,[24] since one direction of the mask is infinitely supported, the storage requirement decreases to $O(M)$, which corresponds to the possible widths of the basis mask patterns. In the method of Yu *et al.*,[25] the convolutions of all the upper right rectangles with kernels in the support region are stored, which is similar to Cobb and Zakhor's method, so the storage requirement is also $O(M^2)$. Therefore, compared with the previous methods, the proposed approach results in a lower storage requirement without sacrificing computational speed, since only several times of lookups, square and sum, are required to compute the aerial image. It is obvious that this approach can dramatically decrease the storage capacity by significantly reducing the number of basis patterns previously required.

In practical applications, it is impossible to implement the convolution of an infinitely supported 2D function with a kernel directly by Eq. (10), because an infinite 2D function cannot be represented as a finite storable matrix. Fortunately, a full-chip mask is always divided into many design patterns before the aerial image simulation is applied, and the range of each design pattern in a single simulation is finite. Moreover, the values of the kernels in a spatial domain decrease dramatically and can be truncated in a certain range. Thus, there exists a safe ambit for each single simulation. As shown in Fig. 3(a), supposing the width of the design pattern is W and the safe ambit radius is A, we only need to perform the simulation in the range of $W + 2A$. As shown in Fig. 3(b), the design pattern is decomposed into the sum of several shifted basis patterns, and the vertex of each shifted basis pattern should be located within the range of the design

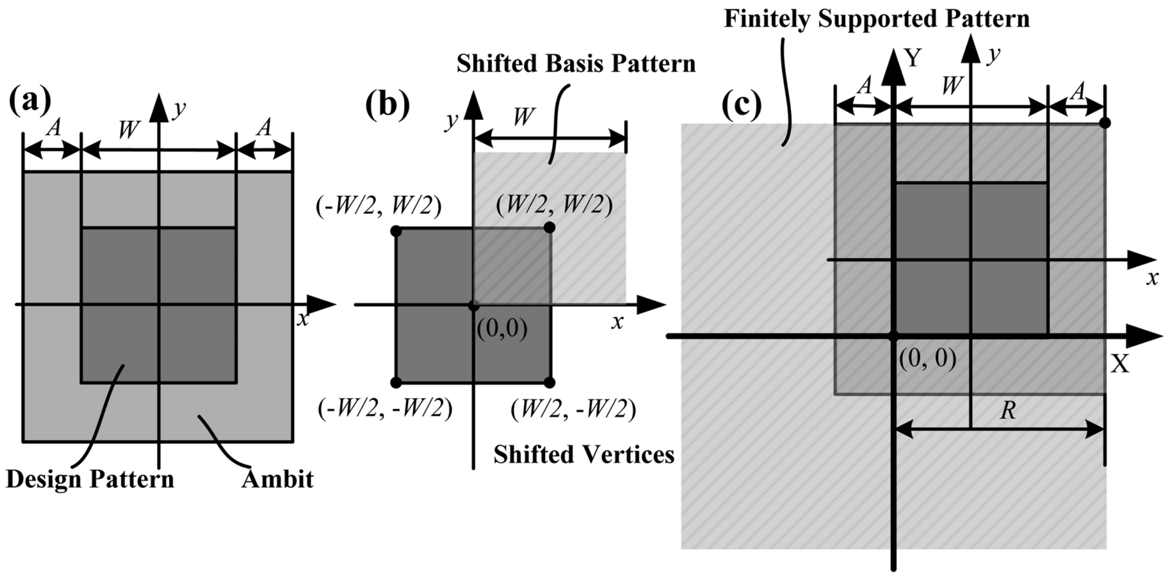

FIG. 3. Illustration of the finitely supported basis pattern that is used to replace the infinitely supported basis pattern. (a) The design pattern with a width of W and an ambit of A, (b) the shifted infinitely supported basis pattern, and (c) the finitely supported basis pattern.

pattern. Therefore, as shown in Fig. 3(c), in order to obtain the convolution result of the design pattern, the following basis function $\tilde{U}_0$ with a finite support is adequate to replace the infinitely supported basis pattern:

$$\tilde{U}_0(x,y) = \begin{cases} 1, & 0 \le x \le R, 0 \le y \le R \\ 0, & \text{otherwise} \end{cases}, \tag{11}$$

where $R = W + A$ is the finite support range of the supported basis function.

Note that by using such a finitely supported basis pattern, it is only necessary to calculate and store the convolution of the finitely supported basis pattern in the range of $[-W, W]$ so that the aerial image of the design pattern with a width of W can be finally obtained. However, from Eq. (11), it is obvious that the convolution of the finitely supported basis pattern with each kernel has a finite support larger than $[-W, W]$. Therefore, we can truncate this convolution in the range of $[-W, W]$ and then store the results within this range into the lookup table.

III. SIMULATION RESULTS

We performed simulations on a partially coherent imaging system with a quasar source illumination whose outer radius is $\sigma_{\text{out}} = 0.8$ and whose inner radius is $\sigma_{\text{in}} = 0.4$. The wavelength in the simulation was set to be 193 nm, and the numerical aperture was set as 0.75. We utilized five eigenvectors of TCC as kernels to approximate this imaging system, and then we generated the lookup table for aerial image simulation by using the above-defined basis pattern. The aerial image simulation range for the design pattern was set for $[-500$ nm, 500 nm$]$ with a grid size of 2 nm, resulting in a width W of 1000 nm in each direction. The ambit radius A was set for 800 nm; consequently, a finitely supported basis pattern in the range of $[-1800$ nm, 1800 nm$]$ was used to replace the infinitely supported basis pattern. The convolutions of the finitely supported basis pattern with the five kernels were calculated in the range of $[-1000$ nm, 1000 nm$]$ with 1001 discrete points in each direction. These convolutions in the lookup table lead to a storage requirement of $5 \times (1001)^2 = 5 \times 10^6$ complex numbers in total, which is acceptable for almost all current computers.

In order to evaluate the accuracy of the proposed approach, we carried out aerial image simulations for two typical mask patterns, namely a five bar pattern and a contact cross pattern. For the five bar pattern, the width of all the bars is 90 nm. For the contact cross pattern, the width of the central contact is 300 nm, and the width of all the surrounding four contacts is 200 nm. All of the simulations were performed on a HPZ800 Workstation of 3.46 GHz Opteron with MATLAB in Windows 7 (64 bit). For the same mask patterns, we made a comparison of the aerial image calculated by the proposed method with the widely used commercial lithography simulation software PROLITH$^{\text{TM}}$. The normalized mean squared error defined to measure the difference between the aerial image calculated by the proposed method and that by PROLITH (Ref. 24) is given by

$$e(A,B) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left|a_{ij} - b_{ij}\right|^2}{\sum_{i=1}^{n}\sum_{j=1}^{m}\left|a_{ij}\right|^2}, \tag{12}$$

where A and B denote the two matrices that represent the aerial images calculated by the two methods, respectively.

As shown in Fig. 4, the contours calculated by the lookup table method fit very well with those provided by PROLITH for both the five bar pattern and the contact cross pattern. In the simulation, the mean squared error is 0.0479% for the five bar pattern and 0.0226% for the contact cross pattern. The differences between these aerial images, which are normalized by the largest intensity, are also shown in Fig. 5.

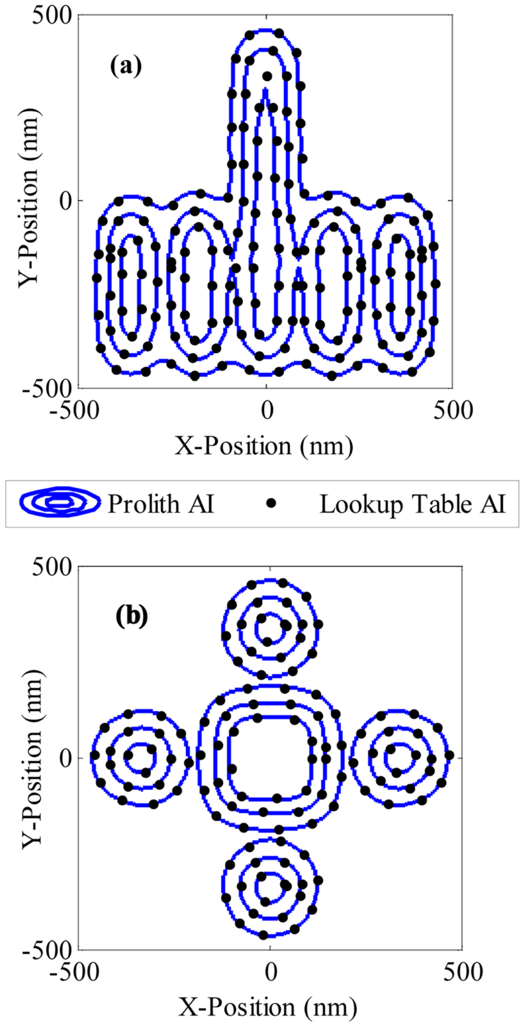

FIG. 4. (Color online) Simulation results of aerial image calculation by the proposed lookup table approach for (a) a contact cross pattern and (b) a five bar pattern.

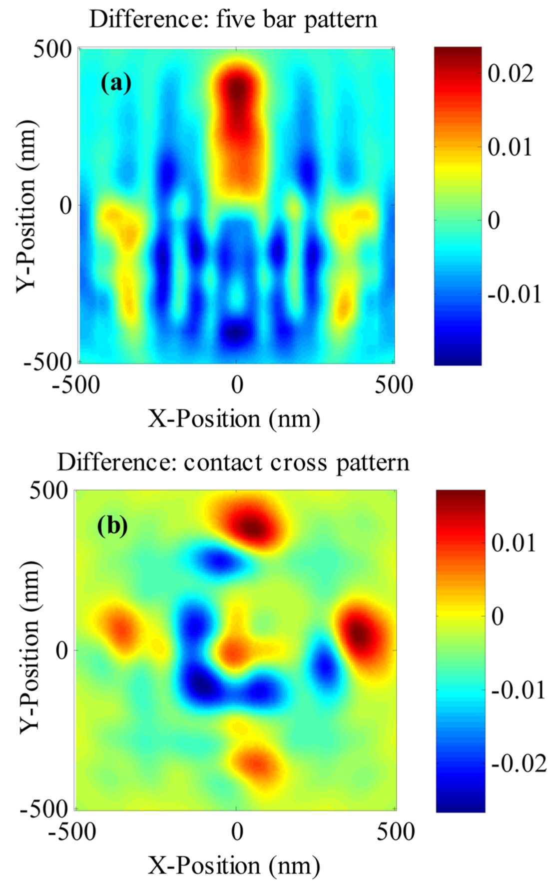

FIG. 5. (Color online) Differences between the aerial images calculated by the proposed method and by PROLITH for (a) the contact cross pattern and (b) the five bar pattern. The values shown are normalized with respect to the maximum image intensity.

The simulation results demonstrate that the aerial images computed by the proposed method have a high accuracy compared with the aerial images computed by PROLITH. It is also noted that the error decays rapidly as the number of kernels utilized in the simulation increases, according to the work of Pati *et al.*[24]

To further demonstrate the efficiency of the proposed approach, we applied it in OPC optimization for several typical patterns, including a U-bar (length = 600 nm, width = 400 nm, and linewidth = 120 nm) and a crossbar (length = 800 nm in x/y direction, and linewidth = 120 nm). The optical parameters in this simulation were the same as in the previous simulation for the comparison of aerial image accuracy. The whole OPC flow shown in Fig. 6 was performed on these two patterns with different fragmentation lengths of 30 and 50 nm. The forward aerial image simulation was performed by the proposed lookup table approach, and without losing generality, a constant threshold resist model was simply introduced to generate the output pattern of the resist image.[26] While the area between the output pattern contour and the desired pattern was defined as the concept of edge placement error (EPE),[22] as shown in Fig. 7, the sum of the EPEs for all segments was introduced as a cost function for evaluating the optimization effect.

The contours of the target pattern, the optimized patterns after ten iterations, and their corresponding output patterns are shown in different line types in Fig. 8. It is observed that the output patterns have a high fidelity with the target patterns in all simulations. Thus the proposed approach is expected to be applicable in OPC systems. The number of lookups for each aerial image computation and the corresponding runtime are shown in Fig. 9 as the edges move to obtain the optimized mask. The simulation results demonstrate that the runtime increases linearly as the number of lookups increases. This is because after several iterations, the optimized masks become more complicated with many more vertices. Therefore, it is shown that the total runtime of aerial image simulation depends on the number of lookups, which in turn is identical to the number of vertices that form the design pattern. In fact, in the lookup table method, the aerial image simulation depends fully on the number of kernels and number of vertices that construct the design mask pattern, with a computational complexity of $O(K \times N)$ for K lookups and N partially coherent kernels.

In Fig. 9, it is also noted that for the last single iteration of mask optimization, as the number of vertices increases, it

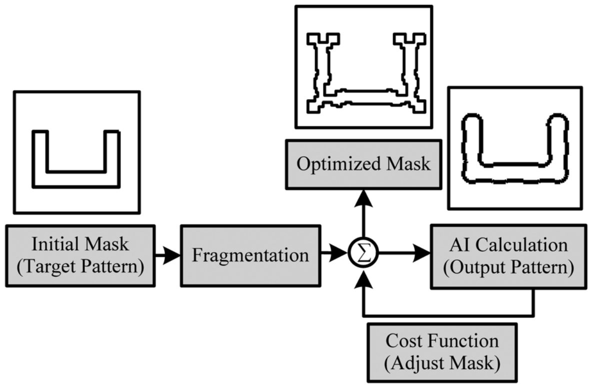

FIG. 6. Flow chart of a simplified OPC optimization process.

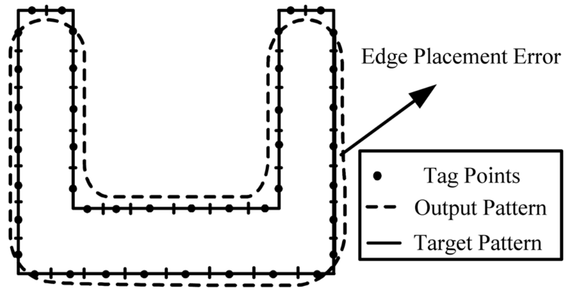

FIG. 7. Fragmentation of the design mask pattern in OPC with tag points defined as the center point of each segment and EPE as the area between the output pattern and object pattern.

needs up to 124 and 144 lookups for the U-bar and crossbar, respectively, and the aerial image computation time is 2.38 s (9.52 μs for a single point) and 2.85 s (11.4 μs for a single point), respectively. This computation time is fairly short, comparable to 300 μs for a single point reported previously in Cobb and Zakhor's method,[21] and about 1 min for a 25.7 μm $\times$ 60.8 μm mask with a grid size of 0.02 μm (15.3 μs for a single point) reported in the method of Pati *et al.*[24] This is due to the fact that the lookup time itself is quite short, and thus the proposed lookup table approach is fast enough to be applied in OPC systems.

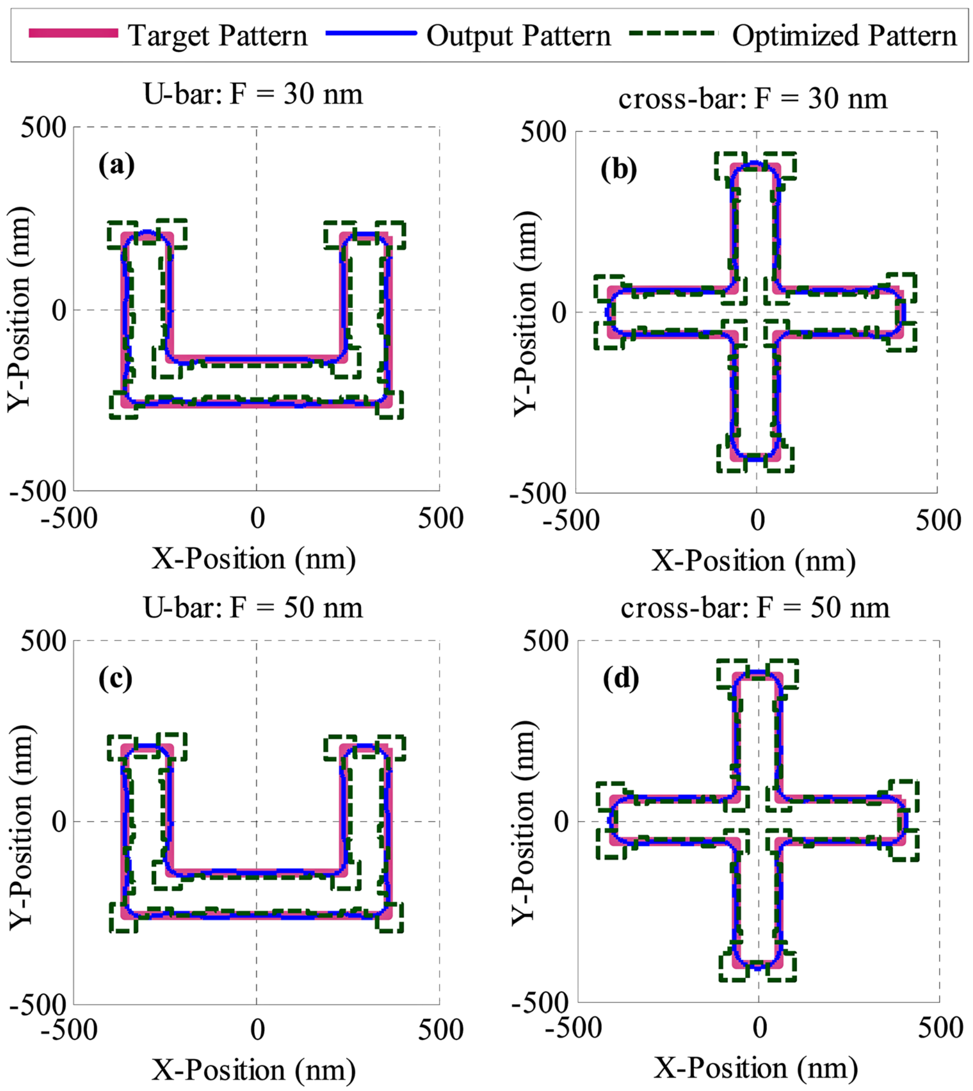

FIG. 8. (Color online) Simulation results of OPC optimization for a U-bar mask pattern and a crossbar. The fragmentation length in (a) and (b) is $F = 30$ nm, and in (c) and (d) is $F = 50$ nm. (a) and (c) are for the U-bar pattern, and (b) and (d) are for the crossbar pattern.

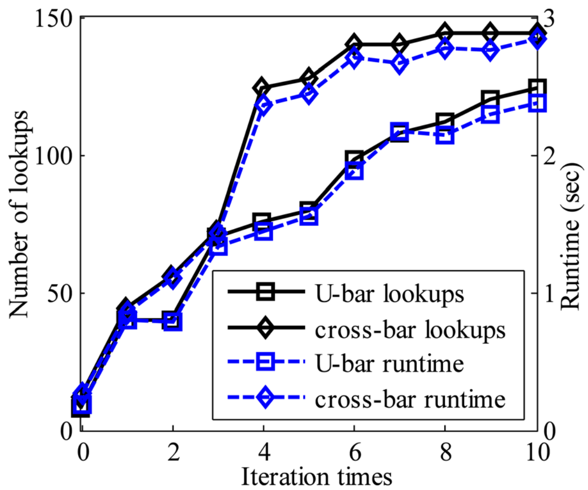

FIG. 9. (Color online) Total runtime and number of lookups in aerial image simulation during OPC optimization process for U-bar and crossbar patterns with fragmentation lengths of 30 nm.

IV. CONCLUSIONS

In this paper, an aerial image simulation algorithm using one basis mask pattern to generate the lookup table is proposed, by defining the basis pattern as an infinitely supported 2D step function and by investigating the translation-invariant property of 2D convolution. It is proved that any rectilinear polygon mask pattern can be decomposed into a series of shifted basis patterns. The convolutions of each shifted basis pattern with the partially coherent kernels can be obtained by shifting the corresponding convolutions of the basis pattern mask with the kernels; thus, only such convolutions of the basis pattern need to be precalculated and stored as the lookup table. Simulations of aerial image computations and OPC applications have demonstrated that the proposed approach is not only able to dramatically decrease the storage requirement, but also is fast and accurate enough to be applied in OPC systems.

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[1]A. K. K. Wang, *Resolution Enhancement Techniques in Optical Lithography* (SPIE Press, Bellingham, WA, 2001).
[2]N. Cobb and A. Zakhor, Proc. SPIE **2440**, 313 (1995).
[3]A. Poonawala and P. Milanfar, IEEE Trans. Image Process. **16**, 774 (2007).
[4]X. Ma and G. R. Arce, Opt. Express **15**, 15066 (2007).
[5]X. Ma and G. R. Arce, J. Opt. Soc. Am. A **25**, 2960 (2008).
[6]X. Ma and G. R. Arce, Opt. Express **16**, 20126 (2008).
[7]S. H. Chan, A. K. K. Wong, and E. Y. Lam, Opt. Express **16**, 14746 (2008).
[8]Y. J. Shen, N. Wong, and E. Y. Lam, Opt. Express **17**, 23690 (2009).
[9]Y. J. Shen, N. N. Jia, N. Wong, and E. Y. Lam, Opt. Express **19**, 5511 (2011).
[10]J. C. Yu and P. C. Yu, Opt. Express **18**, 23331 (2010).
[11]E. Y. Lam and A. K. K. Wong, Opt. Express **17**, 12259 (2009).
[12]H. Hopkins, Proc. R. Soc. London, Ser. A **217**, 408 (1953).
[13]M. Born and E. Wolf, *Principles of Optics*, 7th ed. (Pergamon, Oxford, 1999).
[14]A. K. K. Wong, *Optical Imaging in Projection Microlithography* (SPIE Press, Bellingham, WA, 2005).
[15]E. Kintner, Appl. Opt. **17**, 2747 (1978).
[16]R. L. Gordon, Proc. SPIE **4692**, 517 (2002).
[17]R. L. Gordon and A. E. Rosenbluth, Proc. SPIE **5182**, 73 (2004).
[18]K. Yamazoe, J. Opt. Soc. Am. A **25**, 3111 (2008).
[19]S. Y. Liu, W. Liu, and T. T. Zhou, J. Micro/Nanolith. MEMS MOEMS **10**, 023007 (2011).
[20]S. Y. Liu, W. Liu, and X. F. Wu, Chin. Phys. Lett. **28**, 104212 (2011).
[21]N. Cobb and A. Zakhor, Proc. SPIE **2621**, 534 (1995).
[22]N. Cobb, "Fast optical and process proximity correction algorithms for integrated circuit manufacturing," Ph.D. Dissertation (University of California at Berkeley, 1998).
[23]Y. Pati and T. Kailath, J. Opt. Soc. Am. A **11**, 2438 (1994).
[24]Y. C. Pati, A. A. Ghazanfarian, and R. F. Pease, IEEE Trans. Semicond. Manuf. **1**, 62 (1997).
[25]P. Yu, S. Shi, and D. Pan, J. Micro/Nanolith. MEMS MOEMS **6**, 031004 (2007).
[26]W. Huang, C. Lin, C. Kuo, C. Huang, J. Lin, J. Chen, R. Liu, Y. Ku, and B. Lin, Proc. SPIE **5377**, 1536 (2001).