Computational techniques to incorporate shot count reduction into inverse lithography

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***Abstract*—We develop an inverse lithography method to tackle the shot count minimization in mask fracturing. The shot count minimization in model based fracturing is considered as a problem of finding a sparse combination of basis functions for the mask patterns, where the basis functions are defined as rectangles corresponding to the shots. This problem is formulated as a nonlinear least square problem, and a Gauss-Newton algorithm is proposed to solve it. The algorithm is modified to promote sparsity to reduce the shot count. Preliminary results of mask fracturing using the proposed algorithm is shown, and it is also incorporated into inverse lithography to show its effectiveness to reduce shot count.**

I. Introduction

The shrinking dimension in semiconductor industry necessitate holistic optimization of the lithographic components. Computational lithography such as source mask optimization and inverse lithography are applied due to their strong power to overcome diffraction in the lithographic imaging system [1].

In the inverse lithography, the objective is not only to improve the image quality printed on the wafer plane, but also to design mask patterns that can be friendly to make. Many efforts have been devoted to achieve the latter objective. In mask optimization using gradient based method, regularization terms such as total variation has been enforced to remove the complex components like isolated holes, protrusions [2]. The regularization is extended to wavelet term and local variations on mask edges to render the rectilinearity of the designed mask [3], [4].

Though the regularization method can effectively reduce the complexity of the mask pattern, they still encounter difficulty to take the practical mask writing process into consideration. Usually, the mask is manufactured by the variable shape beam (VSB) writer, which is known to be able to generate only rectangular or triangular beam at each shot. Thus, the masks obtained from inverse lithography undergo a mask data preparation (MDP) process, and are Manhattanized for rectangular writer. The mask making cost is proportional to the writing time, which is dependent on the number of rectangular shots needed. To reduce the shot count, several techniques such as the L-shaped-beam shot are introduced to optimized the mask writers to minimize the shot count to reduce the mask writing cost [5].

In the extremely small dimension, the use of curvilinear shapes becomes of critical to improve the image quality on the wafer plane [6]. However, there is a trade-off between the imaging performance and the mask writing cost [7]. Model based mask data preparation (MB-MDP) method has been proposed for the fracturing and confirmed overlapping shots can reduce the shot count [8]. Recently, the extreme demands of optical lithography make it necessary to consider all the sources in lithography processes can be optimized [9]. This push the desire to consider the mask optimization in inverse lithography and shot count reduction in the fracturing process together. However, the model based fracturing method usually consider these two processes independently, and the fracturing can't provide feedback to the mask optimization.

In this paper, we develop a inverse imaging method for the mask fracturing which is suitable to be incorporated into inverse lithography to provide feedback for mask optimization. The method is based on a basis representation of the mask pattern, in which the basis functions are defined as the rectangles corresponding to the potential shots similar to source mask optimization [10], [11]. This process is formulated as a nonlinear optimization problem, and a sparsity constraint is enforced to reduce the shot count. A Gauss-Newton algorithm with promising efficiency is proposed to solved the problem. Due to similarity of the problem formulation, this method has the intrinsic benefit to be incorporated into the mask optimization in inverse lithography. Simulation is performed to show its effectiveness by comparison with known optimum result, and preliminary results is demonstrated to incorporate it into inverse lithography.

II. Mask Fracturing Formulation

In 22 nm technology and beyond, aggressive resolution enhancement technique such as inverse lithography are required. The objective of inverse lithography is to predistort the mask pattern to improve the image quality on the wafer plane, and it can be formulated as an inverse imaging problem. Let $\widetilde{T}$ to represent a forward process to model the transfer of a mask pattern $M(x,y)$ to the print one on the wafer, the inverse imaging problem can be expressed as

$$M_t(x,y) = \underset{0\leq M(x,y)\leq 1}{\arg\min}\ \mathcal{C}_m\{\widetilde{T}\{M(x,y)\}, I_0(x,y)\}. \qquad (1)$$

where (x, y) is the spatial coordinate, I_t is the desired pattern, $\mathcal{C}_m$ is the cost function to measure the image quality, and M_t is the optimized mask pattern.

After the mask optimization, the mask undergoes a MDP process that partition a mask pattern to a number of shots for mask writing. The VSB currently used for mask writing can generate only rectangular shots. To reduce the writing time, it is critical to reduce the shot count in the fracturing process. Recently, model based fracturing (MBF) is proposed to reduce the shot count with overlapping shots. Several model based fracturing methods are proposed to reduce the shot count while maintaining the image quality on the wafer. A signal reconstruction method is proposed by Jiang and Zakhor which is shown to reduce the shot count while the image quality measured by edge placement error (EPE) is slightly increased [12]. The integer linear programming method is proposed by Tuck *et al.* to refine the shot count, and the algorithm is verified by artificial and realistic benchmarks [13].

However, these methods consider the mask optimization in inverse lithography and shot count reduction as independent processes. The algorithm to recovery a pattern with rectangles is known to be NP hard, and the algorithms can be difficult to be incorporated into inverse lithography. In this paper, we propose an inverse imaging method for mask fracturing, which can be easily incorporated into inverse lithography.

We consider the mask fracturing as the searching of the fewest shots to represent the mask pattern. Each shot is represented as a rectangle function as

$$S(x,y,p) = \begin{cases} 1, & \text{if } |x-x_p| \leq \frac{W}{2} \text{ and } |y-y_p| \leq \frac{H}{2} \\ 0, & \text{otherwise} \end{cases}, \quad (2)$$

where (x_p, y_p) is the center point of the rectangle, and W and H are the width and height of the rectangle. The mask is expressed as the combination of the shots. To allow overlapping of shots, a threshold function is enforced on the linear combination of shots, and thus the mask pattern is represented as

$$M(x,y) = H\Big\{\sum_{p=1}^{K} \alpha_p S(x,y,p), c_h\Big\}, \quad (3)$$

and the threshold function H is defined as

$$H(\phi, c_h) = \begin{cases} 1, & \phi \geq c_h \\ 0, & \text{otherwise} \end{cases}, \quad (4)$$

where c_h is a small value.

Rectangles with different sizes and positions can be combined together to form a shot library. Only the shots with nonzero coefficient contribute in mask writing. The objective of shot count reduction can be considered as the problem to find the fewest nonzero coefficient in mask representation. This problem is the famous sparsity promotion in image processing, and thus the fracturing can be formulated as the following optimization problem

$$\begin{aligned} &\text{minimize } \|\alpha\|_0, \\ &\text{subject to } \|M(x,y) - M_t(x,y)\|_2^2 \leq \sigma, \end{aligned} \quad (5)$$

where the l_0 norm measures the number of coefficients that are nonzero, corresponding to the shot count.

The optimization problem described above is very similar to the sparsity basis pursuit problem in image processing. However, due to the threshold effect, it is intrinsically nonlinear. Thus, it is different from linear basis pursuit, and cannot be solved with related algorithms. We devise a Gauss-Newton algorithm to solve this problem, and modify the traditional iteration process to promote sparsity.

In Gauss-Newton algorithm, the iteration direction δ_k in each iteration is obtained by solving a quadratic problem as [14]

$$\delta_k = \arg\min_{\delta} \, \mathcal{E}(\alpha_k) + \mathcal{J}_{\mathcal{E}}(\alpha_k)\delta + \frac{1}{2}\delta^T \mathcal{H}_{\mathcal{E}}(\alpha_k)\delta, \quad (6)$$

where $\mathcal{E}$ is the objective function, $\mathcal{J}$ and $\mathcal{H}$ are the corresponding Jacobian and Hessian matrix. As the objective function in the formulation can be considered as nonlinear least square, that is

$$\mathcal{E}(\alpha) = \|\mathcal{G}(\alpha)\|_2^2, \quad (7)$$

where $\mathcal{G}(\alpha) = M(x,y) - M_t(x,y)$ in Eq. (5). Thus, the iteration direction can be obtained by solving a linear equation by omitting the second order derivative

$$\delta_k = \arg\min_{\delta} \, \big\|\mathcal{G}'(\alpha_k)\delta + \mathcal{G}(\alpha_k)\big\|_2^2. \quad (8)$$

In order to promote sparsity of the coefficient, we change the searching of the iteration direction to the searching of the next coefficient as [15]

$$\begin{aligned} \delta_k = \; &\arg\min_{\delta} \, \|\alpha_k + \delta_k\|_0, \\ &\text{subject to } \big\|\mathcal{G}'(\alpha_k)\delta + \mathcal{G}(\alpha_k)\big\|_2^2 \leq \sigma. \end{aligned} \quad (9)$$

In this way, the iteration direction can be obtained by taking advantage of the fruitful research of linear basis pursuit algorithm. The sparsity can be promoted without adding any computation for the traditional Gauss-Newton algorithm.

III. Simulation Results

To show the effectiveness of the proposed formulation, we perform simulation of mask fracturing on mask pattern with known optimal. It should be noted though the proposed algorithm can be more efficient compared with other mask fracturing method, the number of potential shots can be huge, and thus the library formed can be extremely large. To make the algorithm tractable with a desktop computer, we limit the shots to be squares with fixed sizes, and focus on the effectiveness of the sparse promotion algorithm.

The fracturing of a typical mask shape is performed in the simulation. The mask with the shape is represented with a 125×125 pixel image, and the size of the pixel is $0.5\,\text{nm}$. The potential shots are set as fixed $23 \times 23\,\text{nm}$ squares. The proposed algorithm is performed to select the squares to represent the mask. After the square is chosen, they are merged to form the rectangles for shots.

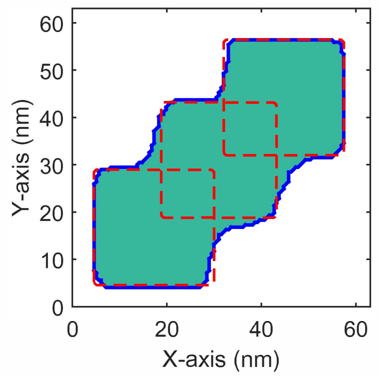

Fig. 1. The mask fracturing result for a typical mask pattern. The blue lines show the contour for the mask shape, and the red lines show the shots.

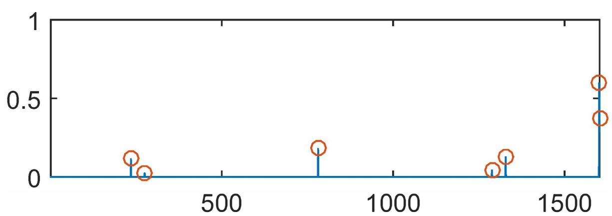

Fig. 2. The coefficients for mask representation. The number of nonnegative coefficient is approximate to the shot count in mask fracturing.

The mask fracturing result with the proposed algorithm is shown in Fig 1, and the corresponding mask representation coefficients are shown in Fig 2. The mask shape is represented with the blue contour, and the shots are represented with red rectangular. It is shown that the fracturing results is similar with the results shown in Ref [13], which is know to be the optimal result. The representation coefficients are shown in Fig 2, in which only few of them are nonzero. This depict only several squares are chosen for the representation among the large number of shot candidates. The slightly different number of coefficients with the shot count comes from the merging after the optimization algorithm.

We also performed simulation of mask fracturing together with mask optimization. The mask fracturing is conducted during the mask optimization in inverse lithography. The inverse lithography is conducted with our previously developed mask optimization algorithm with basis representation [11]. The objective mask pattern is a coarse mask pattern used in our previous work, is still represented with a 201×201 matrix. The pixel size is $4.5\,\mathrm{nm}$, and the feature size of the mask pattern is $45\,\mathrm{nm}$.

The mask optimization results is shown in Fig 3, where the optimized patterns with and without the mask fracturing are shown in panel (a) and (b), and panel (c) and (d) show the corresponding resist patterns on the wafer. It is shown that the optimized mask pattern shown in Fig. 3(b) is less complex than the one shown in (a) with larger smallest feature. However, the main assistant features are preserved to achieve a printed pattern with similar image quality. It should be noted that the optimized mask in Fig. 3 is obtained with slightly more time compared with the one obtained in inverse lithography.

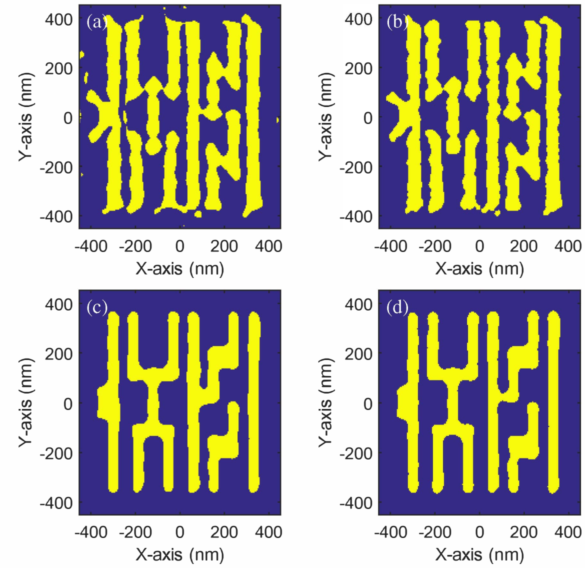

Fig. 3. The optimized mask pattern with and without incorporating the mask fracturing process.

IV. Conclusions

The model based fracturing process in mask data preparation is formulated as a nonlinear least square problem. The optimization problem is then solved efficiently by Gauss-Newton algorithm which can promote sparsity in the iterations. Simulation performed show the proposed algorithm can obtained similar fracturing compared with know optimum, and also demonstrate it can be effective to reduce the mask complexity in inverse lithography.

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