第 24 卷第 12 期 半 导 体 学 报 Vol. 24, No. 12
2003 年 12 月 CHINESE JOURNAL OF SEMICONDUCTORS Dec., 2003

An Efficient Approach to Rules-Based Optical Proximity Correction*

Li Zhuoyuan, Wu Weimin, Wang Yang and Hong Xianlong

(*Department of Computer Science and Technology, Tsinghua University, Beijing* 100084, *China*)

Abstract: A new approach for rules-based optical proximity correction is presented. The discussion addresses on how to select and construct more concise and practical rules-base as well as how to apply that rules-base. Based on those ideas, several primary rules are suggested. The v-support vector regression method is used to generate a mathematical expression according to rule data. It enables to make correction according to any given rules parameters. Experimental results demonstrate applying rules calculated from the expression match well with that from the rule table.

Key words: rules-base; v-support vector regression; OPC

EEACC: 2570 **CCACC**: 7410D

CLC number: TN43 **Document code**: A **Article ID**: 0253-4177(2003)12-1266-06

1 Introduction

As CMOS technology advances, optical enhancement techniques enable optical lithography be close to the resolution limit. However, pattern fidelity of the images on wafer drops due to the optical proximity effects (OPE). One way to overcome the drop is to modify a reticle pattern so that it will produce desired aerial image on wafer. This method is known as optical proximity correction (OPC)[1], which has been seen as an inevitable step of post-processing after layout design. The goal of OPC is to produce smaller features in an IC using a given equipment set by enhancing lithography resolution. It is based on systematic corrections that compensate for the feature distortions arising from optical diffractions[2].

There are two major types of approaches, rules-based[3] and model-based[4] for OPC. In the model-based approach, the required corrections are made according to the lithography simulation results, which are iterated within the correction algorithm. It is regarded as extremely computation intensive and may be troublesome when numbers of features are concentrated in a layout. On the contrary, the rules-based approach derives the required corrections according to a predetermined rule set. The corrections are determined using table lookups by some rules parameters such as layout geometry, substrate, and process phenomena. It is much faster and more practical. For rules-based approach, how to obtain stock of data for various conditions is the key issue. Lack of precise data for each possible parameter may cause errors that could not be ignored when applying the rules in practice.

This fundamental problem could be solved when the rules data table is replaced by a precise

* Project supported by 985 Basic Research Foundation of Tsinghua University and High Technology Research & Development (863) Program of China(No. 2002AA1Z1460)

Li Zhuoyuan male, was born in 1980, PhD candidate. His research interests focus on VLSI layout design.

Received 7 May 2003, revised manuscript received 3 July 2003

mathematical expression between rules parameters and the corresponding required corrections. Then we can easily calculate the correction for any possible combination of parameters. However, it is very difficult to establish a mathematical model between the parameters and corrections. A more practical method is to formularize the rules through recursion methods or regression methods. The recursion methods, such as interpolatory quadrature formulas or least square method, are still dependent on a lookup table when applied. The flexibility and accuracy are restricted because the sampling data in the table may be not representative. Regression method could avoid this problem through iterative computation on the training data to generate a proper model. As a hot machine learning issue, support vector machine (SVM) could achieve similar accuracy with neural networks (NN) after careful data pre-processing. So we choose the v-support vector regression (v-SVR) for our application[5]. It is from LIBSVM, a library for support vector machine that provides an automatic parameter and model selection[6].

2 Rules-based OPC system

Figure 1 illustrates the frame of a rules-based OPC system. In principle, a rules-base approach is a fast and efficient paradigm. Layout geometry, substrate, and process phenomena can be folded into few rules parameters. These parameters define how to compensate the layout for the effect of those phenomena using table lookups or mathematical methods. The rules parameters can be derived from models by optics image simulation, from empirical results or from measurement on the mask. Once they have been derived, they apply for all features on all masks.

Since the corrections for the features are made according to the rules, the selection and construction of rules are essential to the application. There have been different forms of rules for different geometry information of layout patterns. Each form of rule has several parameters to describe the corrections. Thus the correction for any pattern in the layout could be expressed as

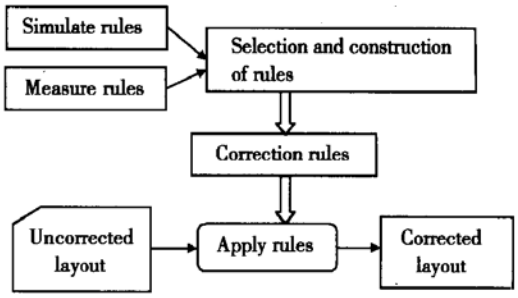

Fig. 1 Elements of rules-based OPC approach

$$\begin{aligned} \delta_i &= \delta(E, F, G_i) \\ E &\in \{\text{edge}, \text{corner}, \text{lineend}, \cdots\} \\ F &= \{\lambda, \text{CD}, \text{defocus}, \text{NA}, \sigma\} \\ G_i &= \{g_{i1}, g_{i2}, g_{i3}, g_{i4}, \cdots\} \end{aligned} \tag{1}$$

where E represents the different forms of rules; F represents the set of optical lithography parameters; G_i represents the set of geometric information parameters in the area around pattern i.

By selecting a value for each parameter in set F, the rule for correcting a special form is related to its geometric information parameters set. The challenge in a rules-based approach is parameterize G_i so that the parameterization could cover a large number of geometric situations. Three forms of rules are suggested in Ref. [3], which are 1D, 1.5D and 2D. However, experimental results show that there are limitations in some rules and the parameters in some rules are redundant. In order to make the rules-base robust and adaptable in a wide range of cases, an improvement is made on the selection and construction of the rules.

2.1 Selection of parameters

More detailed and complicated rules will describe layout more accurately. However, the simulation process and the construction of rules-base will be more complicated. It is necessary to delete parameters that are redundant or with few effects on the precision. Considering this fundamental, we compare different patterns and combinations in some layouts, test many patterns, and finally come up with four primary rule types, which are called as line-width, corner, line-end and hole, respectively.

According to the rules in Ref. [3], there are at least six parameters to describe any pattern. The construction of the rule table will be too time-consuming. Testing and validation on these parameters are done in Ref. [7]. Through comparison with two curves, which represent the simulation results whether the parameter is considered or not respectively, we can account for the influence of this parameter on the correction. Parameters with little influence are ignored. Finally we came to our selection results shown in Fig. 2. Each form of rule has only three parameters.

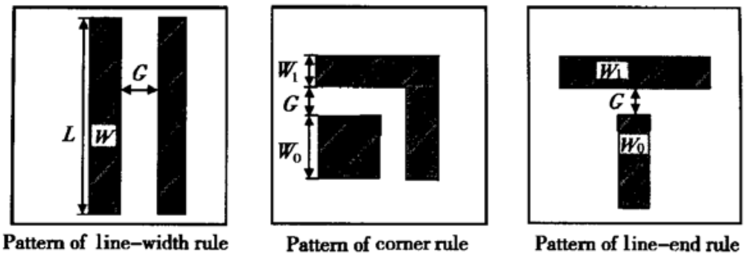

Fig. 2 Three patterns of rules The bold line is the correction target, and other patterns are its environment.

2.2 Construction of rules table

For any rules-base approach, construction of an apropos rules-base table is difficult but essential to the application. Each rule type represents a class of instance. The changes of parameters stand for a series of patterns belonging to the same sort of instance. Though more items in the table will result in more results, the excessive computation load prevents it from application. On the other hand, only corrections corresponding to exactly the same parameter set in the table could be made as accurate as that from model based approach. Other corrections are derived from interpolation. The correction results will be affected because of insufficient sampling items or the deficiency in the interpolation method. Based on these principles, the rules table is constructed with the same method in Ref. [7].

3 v-SVR approach

Typical rules-base approaches determine corrections from table lookup. Corrections corresponding to the parameter sets that are not in the table are made by some mathematical methods such as least square method or even linear interpolation. Deficiency in these methods prevents achieving more accurate results with rules-based approaches. For many instances, the sampling items in the table are not representative. Excessive dependence on these items leads a distortion in the result from real instance.

The v-support vector regression method is applied in our work to make an improvement on the fundamental deficiency of rules-based approach. It is a derivation from the support vector machine theory[8]. It is a new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high-dimension feature space. In this feature space a linear decision surface is constructed. Special properties of the decision surface ensure high generalization ability of the learning machine. Based on this model, support vector classification (C-SVC, nu-SVC), distribution estimation (one-class SVM), and regression (epsilon-SVR, nu-SVR) are generated for different applications.

The formulation of v-SVR is as follows: Given a set of data points, $\{(x_1, z_1), \cdots, (x_l, z_l)\}$, such that $x_i \in R^n$ is an input and $z_i \in R^1$ is a target output, the form of v-support vector regression is

$$\begin{aligned} &\min_{\omega, b, \xi, \xi^*} \frac{1}{2}\omega^T\omega + C\left(v\epsilon + \frac{1}{l}\sum_{i=1}^{l}(\xi_i + \xi_i^*)\right) \\ &\omega^T\Phi(x_i) + b - z_i \leqslant \epsilon + \xi_i \\ &z_i - \omega^T\Phi(x_i) - b \leqslant \epsilon + \xi_i^* \\ &\xi_i, \xi_i^* \geqslant 0 \quad i = 1, \cdots, l, \ \epsilon \geqslant 0 \end{aligned} \tag{2}$$

The dual is

$$\begin{aligned} &\min_{\alpha, \alpha^*} \frac{1}{2}(\alpha - \alpha^*)^T Q(\alpha - \alpha^*) + z^T(\alpha - \alpha^*) \\ &e^T(\alpha - \alpha^*) = 0, \ e^T(\alpha + \alpha^*) \leqslant Clv \\ &0 \leqslant \alpha_i - \alpha_i^* \leqslant C/l \quad i = 1, \cdots, l \end{aligned} \tag{3}$$

where e is the vector of all ones, $C > 0$ is the upper bound, Q is an positive semi-definite matrix of l by l, $Q_{ij} = K(x_i, x_j) = \Phi(x_i)^T\Phi(x_j)$ is the kernel. And training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function Φ.

The approximation function is

$$\sum_{i=1}^{l}(-\alpha_i + \alpha_i^*)K(x_i, x) + b$$

The difficulty of solving the quadratic problem is the density of Q because Q_{ij} is in general, not zero. In LIBSVM, the decomposition method is constructed to overcome this difficulty. Through this method, we can generate a model from rules data. Given the parameters set as the input x, we can get the output as the required correction value through the approximation function.

4 Experimental results

The rules-based OPC system is implemented in C program on Sun Enterprise E450 with 4GB memory. Part of the rules-base table is shown in Table 1 and Table 2. The conditions of optical lithography are as follows: wavelength = 250nm, numerical aperture = 0.5, defocus = 0, partial coherence factor = 0.7, minimum line width = 180nm. The variation of step of parameters is fixed and each parameter is in the range from the ideally minimum value to its upper bound that is large enough to make the correction unnecessary. The rules are derived from an iterative simulation and adjustment process to ensure the accuracy of the sampling data.

Table 1 Part of the line-width rule nm

W	G	L	Edge offset
180	270	1080	12
180	270	1170	12
180	270	1260	24
180	270	1350	24
180	270	1440	19

The correction (Edge offset) represents the offset of the target edge.

Table 2 Part of the outcorner rule nm

W_0	W_1	G	Serif width	Serif overlap
180	180	180	90	15
270	180	180	75	6
360	180	180	84	6
450	180	180	72	10
540	180	180	72	10

The correction (Serif width and Serif overlap) represents the value and position of the serif added to the target corner.

Based on the rule table, we can do the regression process with v-SVR. The kernel function $K(u, v)$ is in the form of a radial basis function. It is written as

$$K(u, v) = e^{-\xi \times |u - v|^2} \tag{5}$$

Proper parameters should be selected for the application of v-SVR. These parameters determine the running time of training process and the accuracy of the approximation function. Many times of iterative computations are performed and compared with select proper parameter set for each form of rule. For example, the tolerance of termination criterion is set to be 0.01 and the parameter ξ of the kernel function is set to 0.00005 for the line-width rule.

Table 3 gives part of the regression result for the line-width rule. There are 1183 rows in the table corresponding to each SV in the kernel. Given a parameter set $S = (W_0, G_0, L_0)$, the required correction of edge offset could be derived from Eqs. (4) and (5):

$$R_{\text{edge}} = \sum_{i=1}^{1183} \text{Ceof}_i \times e^{-\xi \times \varphi(S,\text{SV}_i)} + \text{rh}$$
$$\varphi(S,\text{SV}_i) = SS^T + \text{SV}_i\text{SV}_i^T + (S - \text{SV}_i)(S - \text{SV}_i)^T \quad (6)$$

Table 3 Part of the regression results nm

ith-SV	W	G	L	Coef$i$
1	180	180	450	- 42. 23062229313833
2	180	180	540	43. 81511539015932
3	180	180	720	- 47. 5880106470411
4	180	180	810	36. 91758584793786
…	…	…	…	…
23	180	360	540	- 1. 680233935819992
24	180	360	630	14. 45897842443851
25	180	360	810	- 36. 64080902537259

The values of ξ and rh are 0. 00005 and - 14. 6897 respectively. There are 1183 SV in this model.

To show the effectiveness of our method, we applied it to a set of random testing cases. Experimental results are reported and compared with table lookup with linear interpolation in Table 4. The correction values derived from the two methods are compared with the required corrections from an accurate model-based approach. The results are divided into two parts: rules with the parameter set exactly in the table and outside the table. Obviously, for the first part, it will not cause any error with the table lookup method. It is shown that for the v-SVR method, most of the corrections are also correct without deviation. This is because the deviation on the training data is minimized for the machine learning method. For the parameter sets that are not in the table, v-SVR achieves more accuracy than table lookup. Both the average and the maxium error ratio of corrections are well scaled down by v-SVR. It may be that the sampling data in the table are not representative, so the interpolation method could not achieve a good result. Since there is not such a mathematical model to determine which data are appropriate and representative, it is too difficult for the table lookup method to get an improvement on the accuracy.

For the total amount of corrections that exist error, the table lookup method achieves a better result. It is because that in order to achieve a global view on the sampling data, v-SVR gives an approximate solution to reflect any possible variability on the solution space. This prevents it from an accurate solution on a given instance, because the solution space is too complex to simulate. But it could give a good approximation for every instance.

Table 4 Experimental results on edge offset rule

Method	Table items#	Test items#		For items in the table		For items outside the table		
		In-T	Out-T	ErNum	ErRatio	ErNum	ErRatio	MaxEr
v-SVR	1183	1183	753	5	11. 47%	310	11. 06%	54. 39%
Table lookup				0	0. 0	123	24. 59%	100%

In-T/Out-T: testing items with parameter set exactly in the table/outside the table; ErNum: the amount of corrections that are different from the value derived from model-based approach; ErRatio: the average percentage error of corrections; MaxEr: the max percentage error of corrections

5 Conclusion

A new approach for rules-based OPC is presented in this paper. Different from the table lookup method in typical rules-based system, the application of rules is derived from the pre-processing mathematical expression between the parameter sets and required corrections. The efficient validation, selection and construction on rules provide a set of precise sampling data for the training with v-support vector regression process. Special properties of the v-SVR method ensure a high accuracy on the decision surface. Experimental results compared with traditional table lookup method show the effectiveness of our approach.

References

[1] Chen J F, Laidig T L, Wampler K E, et al. Practical method for full-chip optical proximity correction. SPIE, 1997, 3051: 790

[2] Kahng A B, Pati Y C. Subwavelength optical lithography: challenges and impact on physical design. In: IEEE International Symposium on Physical Design, 1999: 774

[3] Otto O W, Garofalo J G, Low K K, et al. Automated optical proximity correction-A rule-based approach. SPIE, 1994, 2197: 278

[4] Shioiri S, Tanabe H. Fast optical proximity correction: analytical method. SPIE, 1995, 2440: 261

[5] Chang C C, Lin C J. Training v-support vector classifiers: theory and algorithms. Neural Computation, 2001, 13(9): 2119

[6] http: //www.csie.ntu.edu.tw/~ cjlin/libsvm/

[7] Shi R, Cai Y C, Hong X L, et al. The important works about the rules in rules-based optical proximity correction. Chinese Journal of Semiconductors, 2002, 23(7): 701

[8] Cortes C, Vapnik V. Support-vector network. Machine Learning, 1995, 20: 273

一种新的光学临近校正方法*

李卓远　吴为民　王　旸　洪先龙

(清华大学计算机科学与技术系, 北京　100084)

摘要: 提出了一种新的光学临近矫正算法. 首先建立了一套高效并且适用性强的规则描述, 然后提出了一种新的规则运用方法. 算法在规则数据表的基础上通过 v-SVR 方法建立规则描述同矫正数据之间的数学表达式, 使得对于任意输入的规则描述都能够精确计算出相应的矫正数据. 实验结果表明, 该算法比传统的查表插值方法具有更高的精度.

关键词: 基于规则; v-SVR; 光学临近校正

EEACC: 2570　　**CCACC**: 7410D

中图分类号: TN43　　**文献标识码**: A　　**文章编号**: 0253-4177(2003)12-1266-06

* 清华大学985基础研究和国家高技术研究发展计划(No. 2002AA1Z1460)资助项目

李卓远　男, 1980年出生, 博士研究生, 从事VLSI布图设计工作.

2003-05-07 收到, 2003-07-03 定稿