An effective method of contour extraction for SEM image based on DCNN

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***Abstract*—SEM-image contours provide valuable information about patterning quality and capability. Geometrical properties such as critical dimension and resist sidewall angle could be extracted or estimated from SEM image contours. Those geometrical properties can be used for OPC model calibration, OPC model verification and lithography hotspot detection. This work presents a machine learning based method for contour extraction of SEM image. A designed DCNN network and self-made high quality dataset are combined for contour model training. Based on the high capability of image/feature representation and remarkable advantage of parallel computing with hardware acceleration, the model achieves high accuracy and real-time operation for contour extraction, more importantly, it provides the ability to distinguish and separate the top and bottom contours of SEM images. Additionally, the model not only removes the abundant edges but also repairs the local discontinuity caused by imperfect process and measuring technique.**

Keywords—SEM images, contour extraction, machine leaning (ML), deep convolution neural network (DCNN)

I. INTRODUCTION

CD measurement data from SEM images are widely used in OPC model training [1-2]. As the complexity of the lithography process increases, only CD measurement data at discrete locations cannot meet the stringent modeling accuracy requirements imposed on OPC model. Therefore, the contour data based modeling method is proposed in recent years [3-5]. From the perspective of information content, the contours of SEM image can offer much richer information in terms of pattern coverage, and much more stable model in terms of model parameters' uncertainty reduction. Those decisive advantages have led to gradual adoption of OPC model calibration by incorporating SEM image contours. In addition, with extracted contours, both resist top contours and resist bottom contours, feature width and spacing between features, and resist sidewall can easily be estimated, which facilitates the lithography hotspot detection with improved certainty.

In current low K1 lithography processes, SEM images are intrinsically low contrast, the situation exacerbates when only few scanning frames can be averaged in order to avoid resist shrinkage. This presents enormous challenges for contour extraction from SEM images, it is particularly true at locations where patterns are close to failure. The traditional methods utilizing edge operators, such as Sobel, Prewit, log, etc., are not capable of extracting contours from low contrast SEM images with required robustness; In this regard, the Canny algorithm provides contours with high precision and improved robustness, but it lacks the ability to distinguish resist top contours from resist bottom contours. The fundamental limitation of classical methods of image contour extraction lies in its use of information. All classical methods use very local information only. To overcome the limitation, information more global should be made full use of. Different from images of natural scenes, images from lithography SEM only have three distinct areas, the resist area, the subtract area, and the edge area with varying slopes. By realizing this simplicity and exploring information in a wider spatial area to reduce image noise impact on contour extraction, we have proposed a fast and efficient DCNN structure for contour extraction in this study, which possesses characteristics as wide receptive field, image resolution preserving and moderate in depth.

II. PROPOSED METHOD

A. The Neural Network Architecture

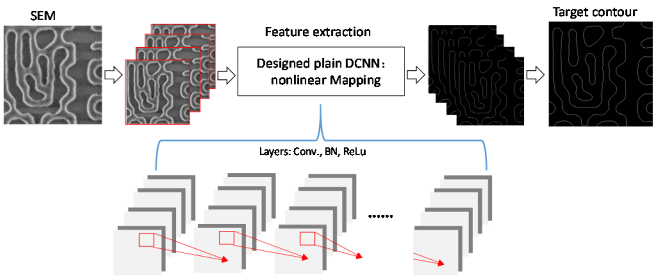

Fig. 1. The designed plain DCNN structure for contour extraction of SEM images.

The neural network architecture is shown in Fig. 1. The first layer is reversible down-sampling operation, used to lower the dimensions for input SEM image. The split sub-images are arranged with a stack format as input of the following module (plain Deep Convolution Neural Network,

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DCNN). For instance, if the down-sampling factor is set 2, then the input image (f_d) of DCNN is: M/2×N/2×4C, where M and N are the height and width of the original SEM image, and the C represents color space channel (gray image: C=1, color image: C=3).

The DCNN module acts as a non-linear mapping from SEM image to contour. In order to learn the mapping function, the DCNN module extracts features of input image with convolution operators. By cascading the convolution layers, high level features could be extracted. Then, the weights of network are adjusted according to the deviations between result and target contour with back propagation (BP) algorithm. To set a learning rate and a proper threshold for loss function, the network could learn some proper parameters for nonlinear mapping.

The DCNN module in Fig. 1 is mainly constructed by many convolution layer as well as some post processing operators such as linear rectification operation (ReLU) and batch normalization (BN) [6]. In detail, each convolution layer is taken as a feature extraction unit, which includes operations of convolution (Conv), ReLU and BN. In particular, the first convolution layer of DCNN module contains only Conv + ReLU. The middle layers contain Conv, ReLU and BN at the same time, since after Conv, the statistical distribution of the original image data will be changed generally, and the statistical deviation/shift will be amplified by the cascading structure, resulting in a local minimum during the optimization and unable to further improve. And the last layer only uses Conv. Zero padding is used to complete the pixel loss and keep full resolution after each layer. The size of output from DCNN module is the same as M/2×N/2×4C. The final image is up-sampled with 4C components to recover the original size M×N×C.

B. Receptive Field

The nature of image processing tasks is restoration/ extraction some 'useful' information from the degraded /corrupted original image which is usually a high dimensional signal. In fact, it is a very challenge task and great effort has been made, until now, several theories have been proven to be effective, in which the sparse representation is of a highlighted one. From the sparsity view of point [7], the sparser the image representation is, the better the image restoration is. And empirically, a large receptive field could make a better sparse representation based on the image priors of nonlocal self-similarity (NSS).

The DCNN is superior to the traditional methods because of its ability to achieve a large receptive field and higher sparsity with powerful feature extraction. In this work, down-sampling is performed at the first layer of network. This operation could double the receptive field (2x). For example, if the layer number is set 15 and the convolution kernel is 3x3, the receptive field is equal to 63x63 while the computational burden is just as 31x31. This is a meaningful and remarkable step for deep learning, which achieves a large receptive field and high computing efficiency at the same time.

C. Plain Structure

The proposed architecture is a plain cascading form which does not use the residual connections. Usually, the residual connections could make a better performance on convergence, however, the final effect is little difference compared with non-residual connections for some deep plain networks [8]. It is expected to design a moderate depth plain neural network with some advanced optimization techniques such as ReLU, BN and Adam [9] to achieve a good performance, furthermore, the simplicity of the plain structure gains faster speed in training which is also very important in applications by using neural network models.

III. EXPERIMENT

To train the DCNN network for contour extraction, we need a high quality training dataset. However, the original SEM images are noisy and with many defects such as scums, neckings, bridgings, etc.. Some image processing techniques have been used in preparing the contour model dataset, such as image denoising and contour refinement. The dataset is splited for training : verification : test with the ratio 6:2:2. The main network parameters used in this work is: down/up sampling rate: 2, number of layers: 15, feature mapping (channels): 64, training area size: 128x128 (cropped from the original image), convolution kernel size: 3x3, batch size: 16.

A. SEM Image Denoising

Due to low K1 lithography processes, SEM images are intrinsically low contrast and noisy, it is very difficult to extract the contour information based on the raw data. Denoising should be performed before contour extraction. And the denoising operation should remove the noise as much as possible while retaining useful information (details) as much as possible at the same time. Another sophisticated neural network has been applied to obtain satisfactory results , as shown in Fig. 2. The structure detailed information can been retained successfully and the residual noise map indicates that no structure/detail information is erased during denoising process from visual inspection and statistical analysis.

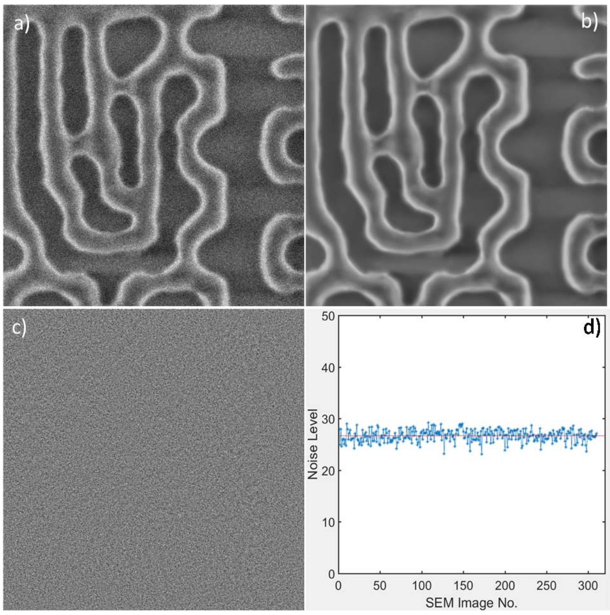

Fig. 2. Denoising results: a) the original noisy SEM image; b) the denoised (clean) image; c) the noise map; d) the noise level distribution of SEM images in dataset, the image intesity range is [0 255].

B. Contour Refinement

For supervised learning, the performance of NN has a close relation with the quality of dataset. A high quality dataset is essential for successful model training. Unfortunately, there are few ground-truth data that we can get in many fields of image processings, such as inpainting, super-resolution, denoising, contour extraction, etc..

In this work, the contour training pair of SEM image is made by a traditional method Canny with some improvements based on some image priors such as the grayscales difference, topological structure for different parts, and length clustering of different contour parts, etc.. It should be pointed out that all the training and testing SEM images are of the denoised version. Two training datasets are prepared for top and bottom model, separately.

IV. RESULTS & DISCUSSIONS

The bottom and top contour models are trained independently based on the prepared datasets. The learning rate is set at 5e-4, and training error patient is fixed at 20, if the training error stays unchanged in sequential 20 epochs, then the parameters of each batch are merged to form the model. Other parameters are used as default in Adam. General data augmentation such as mirror and flip are adopted. The bottom and top model training have been done in ~10 and 18 hours with single GPU, respectively. Then, the model with best performance is selected for testing. Although the model training is usually time-consuming from several hours to days even with GPU acceleration while the testing is very fast with speed of ~ 50ms/frame with single CPU only. The trained model can be easily embedded in some real-time applications with high performance hardware assistance.

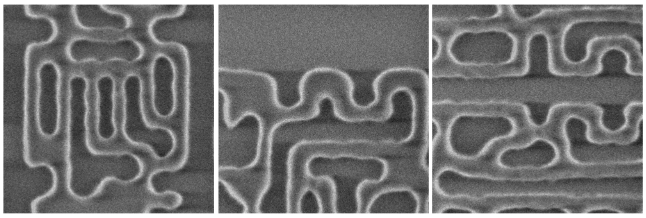

Fig. 3. Some examples of original SEM image pattern.

The test dataset includes post lithography SEM images with necking and bridging of varying degrees, some examples are shown in Fig. 3. Because there is no industry standard for contour extraction algorithm quality assessment, the contour extraction algorithm is evaluated by Fab-centric criteria instead. These criteria include : i) do not miss contour in a visually distinct boundary; ii) do not produce fake contour in background or foreground; iii) flexibility and capability of repairing broken contours if the broken segments gap is small; iv) the contour extraction algorithm should be fast enough to support Fab production needs.

This part summarizes the results for test dataset by using the top contour and bottom contour extraction models. The areas with relatively large "broken" gap between contour segments are identified as "broken" contours; and "fake" contours are identified as "false" contours.

Our test results indicate that the bottom contour extraction model can achieve much better result than the top contour extraction model, with only few percentage of "broken" and "false" contour areas. By no means does it implies that the top contour extraction model is bettern, rather, this is because the boundary between resist and substrate is usually defined bettern than resist sidewall and resist top surface (often rounded).

A. Top & Bottom Contour Identification

A typical result for contour extraction is illustrated in Fig. 4. A complicated 2D pattern with heavy noise and some distortions such as necking, etc., is shown in Fig. 4 a), Fig. 4 c) and d) is top (white) and bottom (yellow) contour results, respectively. Fig. 4 b) is a simple stack of top and bottom contours on the original image for quality check, which claims high fidelity and consistency with the original image structures.

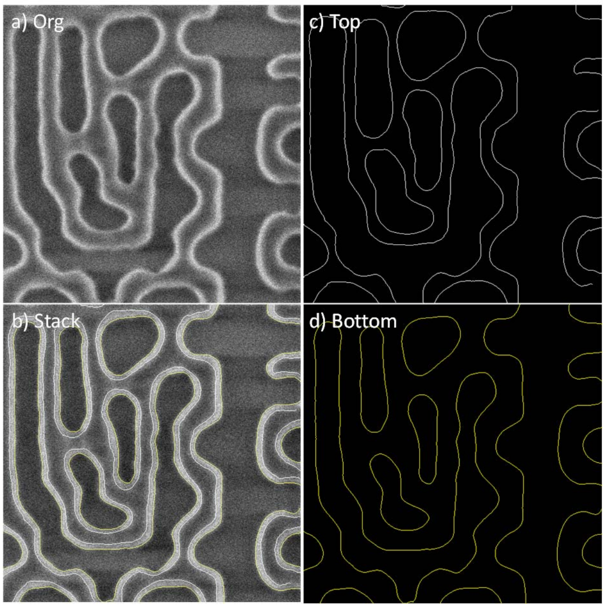

Fig. 4. Top & Bottom contour extraction results: a) the original noisy SEM image; b) the total stack of original image, top contour and bottom contour; c) the top contour; d) the bottom contour.

Furthermore, the DCNN-based method achieves other two 'unexpected' effects: suppressing the redundant edges and "repairing" broken contours within a local area, in comparison with those from "traditional" methods, such as the Canny algorithm, as shown in Fig. 5. Canny algorithm is a landmark in contour extraction field which has been prevalent for several decades because of its simplicity (non-maximum suppression of gradient) and efficiency. However, when a structure is complicated or not in good condition, e.g. the boundary is not clear or continuous, Canny algorithm often fails to obtain a satisfied result. The main reason is that Canny algorithm has a small receptive field (the default mask is 3x3) and simple rule (thresholding) to judge/distinguish different features.

Detailed comparison with Fig. 5 a), b) and Fig. 5 c), d) reveals that DCNN offers two remarkable and decisive advantages besides the ability to separate the top and the bottom contours: 1) the local broken contour could be repaired, as shown in a) and c) (solid yellow boxes), however, if the broken is caused by defect such as 'bridge' which distorts the structure, it is hard to repair (dashed yellow boxes); 2) the false contour caused by the next layer could be suppressed effectively by DCNN while Canny is misled and judges it as a 'reasonable' edge just based on gradient in a local area. Last but also important in real applications , the processing is fast enough because of its parallel optimization mechanism with GPU acceleration.

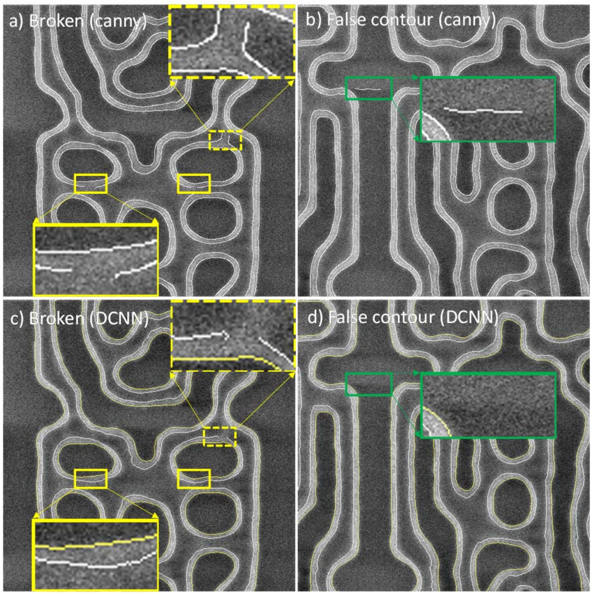

Fig. 5. The display of ‘Broken’ repair (yelow boxes, Fig. 5 c)) and ‘false contour’ suppression (green boxes, Fig. 5 d)) obtained by DCNN method as compared with Canny algorithm Fig. 5 a) and b).

B. *Top & Bottom Contour Extraction Efficiency Difference*

The top and bottom models demonstrate different efficiency in contour extraction. The efficiency difference can be understood if we examine the SEM images and look at the differences between the top and bottom boundaries. Top and bottom contours are from two boundaries, the bottom contour is from the boundary between the wafer substrate and resist sidewall, and the top contour is from the resist sidewall and the resist top surface.

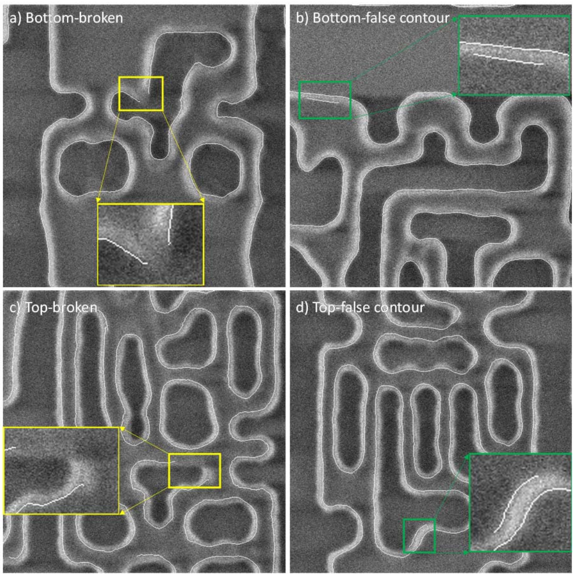

Fig. 6. The display of ‘broken’ (yelow boxes) and ‘false contour’ (green boxes) obtained with top and bottom models, a) and b) are bottom results, c) and d) are top results.

Due to the different scattering characteristics of the electrons from the wafer substrate material, the resist material, and 3D structure details, different regions in SEM image exhibit different gray intensities, resulting in the transition from wafer substrate to resist sidewall is much sharper than that from resist sidewall to resist top surface. Furthermore, the rounded transition from the resist sidewall to the resist top surface causes great ambiguity for edge definition. Therefore, the bottom boundary is usually easier to define/identify than the top boundary.

There are still some ‘broken’ and ‘false contour’ existing in both contour sets, as shown in Fig. 6. The false contours, not related to the next layer, are mainly caused by the highly similar environment between top and bottom areas, and the model is unable to distinguish them. As for broken contours, they are mainly caused by scums. Both “broken” contour areas and “false” contour areas are marked out as flags for Fab engineers to do further closer visual inspection.

V. CONCLUSIONS

In this work, a specially designed DCNN structure is applied for contour extraction from post lithography SEM images. The DCNN not only provides a large receptive field and low demand on computational resources, but also achieves satisfactory results for contour extraction purpose in terms of accuracy and speed. More importantly, the models are able to distinguish and separate the top and the bottom contours. This machine learning based contour extraction methodology provides a powerful mean for further detailed lithography patterning quality assessment, such as estimation of feature width, spacing between features, resist sidewall, PV-band and etc., it also facilitates the lithography hotspot detection with improved certainty.

REFERENCES

[1] A. Yen, P. Tzviatkov, A. Wong, et al., “Optical proximity correction for 0.3um i-line lithography”, Microelectronic Engineering, vol. 30, pp. 141-144, 1996.

[2] A. Yen, M. Burkhardt, J. R. Hzhoefer, et al., “Optical Proximity Correction and its Application to CD Control in High-speed Microprocessor”, Microelectronic Engineering, vol. 41/42, pp. 65-70, 1998.

[3] P. Filitchkin, T. Do, I. Kusunadi, et al., “Contour Quality Assessment for OPC Model Calibration”, Proc. of SPIE, vol. 7272, pp. 72722Q-1-7, 2009.

[4] T. Shibahara, T. Minakawa, M. Oikawa, et al., “A CD-gap-free contour extraction technique for OPC model calibration”, Proc. of SPIE, vol. 7971, pp. 79710O-1-8, 2011.

[5] L. Schneider, V. Farys, E. Serret, and E. Fenouillet-Beranger, “Framework for SEM contour analysis”, Proc. of SPIE, vol. 10145, pp. 1014513-1-14, 2017.

[6] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in International Conference on Machine Learning, 2015.

[7] L. Zhang, and W. M. Zuo, “Image Restoration: From Sparse and Low-Rank Priors to Deep Priors”, IEEE Signal Processing Magazine, Vol. 34, pp. 172 – 179, 2017.

[8] K. Zhang, W. M. Zuo, S. H. Gu, et al., “Learning Deep CNN Denoiser Prior for Image Restoration”, in IEEE Conference on Computer Vision and Pattern Recognition, 2015.

[9] D. Kingma, and J. Ba, “Adam: A method for stochastic optimization,” in International Conference for Learning Representations, 2015