Deep learning's impact on contour extraction for Design Based Metrology and Design Based Inspection

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ABSTRACT

With the miniaturization of devices, hot spots caused by wafer topology are becoming a problem in addition to hot spots resulting from design, mask and wafer process, and hot spot evaluation of a wide area in a chip is becoming required. Although DBM (Design Based Metrology) is an effective method for evaluating systematic defects of EUV lithography and multi-patterning, it requires a long time to evaluate because it is necessary to acquire a high-SN SEM image captured by low-speed SEM scanning conditions. Therefore, by applying deep learning which demonstrates overwhelming performance in the field of pattern recognition, we propose a contour extraction for DBM that can handle low-SN SEM image captured by high-speed SEM scanning conditions.

Contour extraction using deep learning possesses high noise immunity and excellent pattern recognition ability, and demonstrates high performance to contour extraction from low SN SEM images and multiple layers pattern ones. The proposed method is composed of annotation operation of SEM image samples, training process using annotation data and SEM image samples, and contour extraction process using the trained outcome. In the evaluation experiment, we confirmed that satisfactory contours are extracted from low SN SEM images and multiple layers pattern ones.

Keywords: Contour Extraction, DBM, CD-SEM, Deep Learning

1. INTRODUCTION

DBM (Design Based Metrology)[1] is an effective method for evaluating systematic defects, CD (critical dimension) measurement, OPC (optical proximity correction) calibration and EPE (edge placement error) measurement, by making a comparison between contours in SEM images extracted by image processing and corresponding reference patterns such as design patterns, golden dies and so on. Precise contour extraction is a key factor for DBM to demonstrate high performance, but it is going to be more difficult with the miniaturization of devices which involves high-speed scanning conditions for imaging wide areas in a chip and multiple layers patterns in SEM images.

For enhancement of DBM, we propose application of deep learning for enhancing contour extraction performance. Generally, deep learning possesses high noise immunity and flexible pattern recognition ability in the filed of pattern recognition, and in this application shows good performance against low-SN SEM images and complex multiple layers patterns. We assume two stages in contour extraction process for DBM as shown in Figure 1, extraction of IBC (Image Based Contour) and MBC (Measurement Based Contour)[2]. The former extracts initial contour from SEM images. The latter extracts dedicated contour from SEM images using a method based on line-profile analysis, which possesses integrity with shape analysis applications afterward referencing a design data and so on, such as EPE measurement, EPE analysis, contour alignment and so forth. In the scope of this paper, we apply deep learning to the former. We assume that the former could tolerate somewhat difference of contour shapes from conventional image processing, because the latter could absorb the difference and keep the integrity with shape analysis applications afterward.

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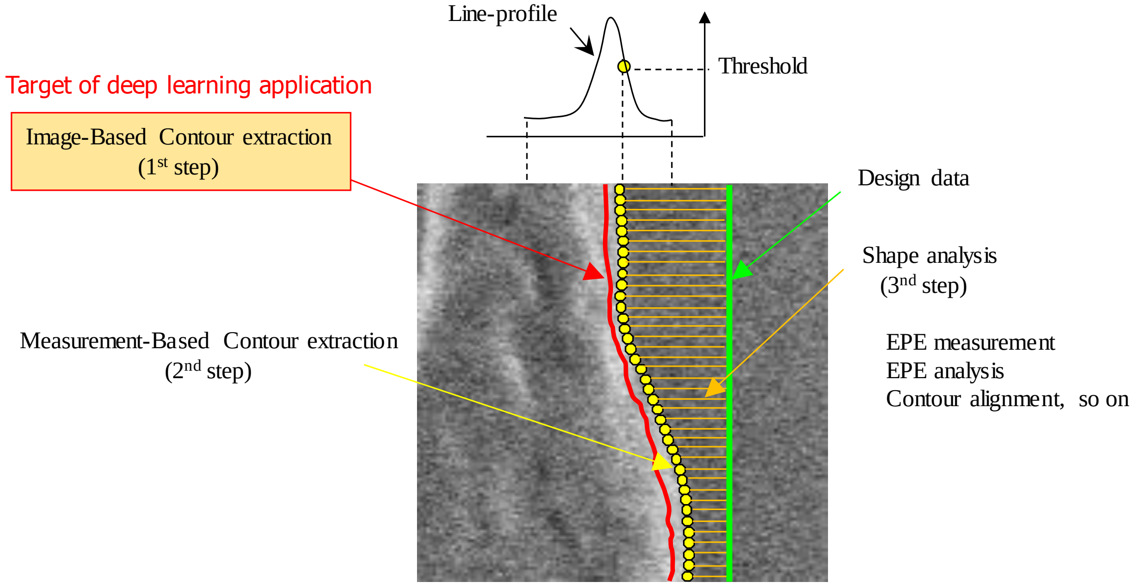

Figure 1. Target of deep learning application in DBM method within this paper.

2. METHODOLOGY

Methodology of the proposed method is described in this section. After mention of the outline, annotation operation, training process and inference process are described.

2.1 Outline of the proposed method

From many kinds of applications using deep learning, we select semantic segmentation for contour extraction, which discriminates a category of each pixel and segments images semantically. Semantic segmentation has been applied to many fields of research such as automotive use [3], medical use [4] and further improvement is currently ongoing [5]. Semantic segmentation has an advantage that it can handle arbitral kinds of shapes flexibly, regions such as polygons and manifolds, and segments such as isolated lines and boundary of regions by discriminating categories of each pixel independently.

The outline of the proposed method is shown in Figure 2. It takes a conventional machine learning scheme, offline annotation operation and training process, and online contour extraction process. In the annotation operation, a label from predetermined categories including a contour is assigned to every pixel in SEM image samples collected previously. In the training process, machine learning optimization is executed to achieve a trained model which is consisted of many parameters in a deep learning network by minimizing errors between the annotation data and contours inferenced from the SEM image samples. In the contour extraction process, contours are inferenced from a given SEM image using the trained model.

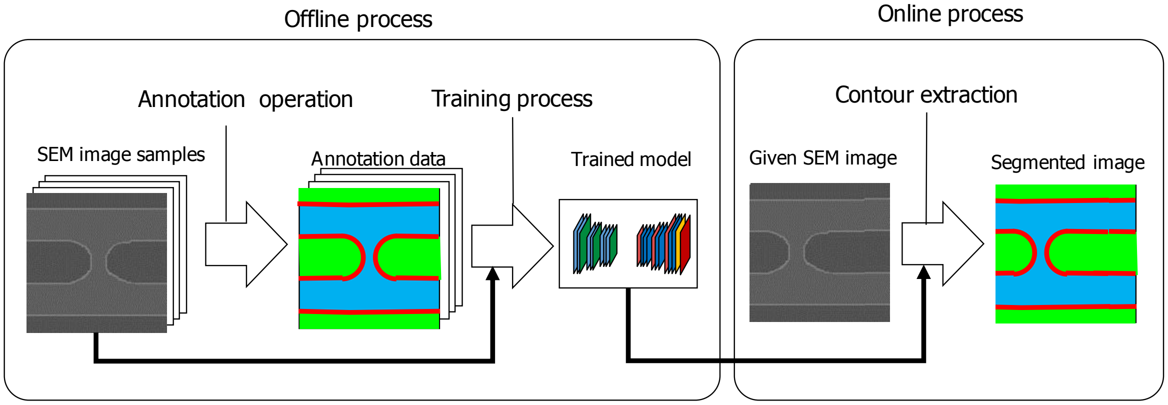

Figure 2. Outline of the proposed method.

2.2 Annotation operation

In the annotation operation, a label in predetermined categories is assigned to every pixel in SEM image samples collected previously. The categories are consisted of contour, background, and enclosed region by any contour. Assignment of a label can be done with any paint tool as shown in Figure 3. Labor for this annotation increase in accordance with number of SEM images, but there are some methods which cut down this labor such as human in the loop approach [6], in which training using subset of samples, inference of others and manual correction of the inference iteratively.

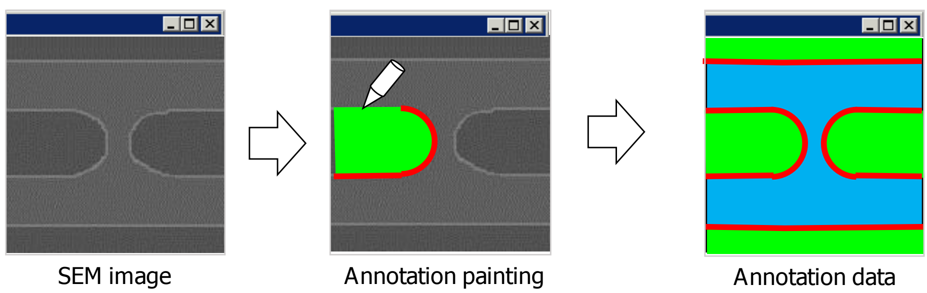

Figure 3. An example of annotation operation for contour extraction.

2.3 Training process

In the training process, machine learning optimization is executed to achieve a trained model by minimizing errors between the annotation data and segmented images inferenced from the SEM image samples.

Approximate structure of the network is shown in Figure 4. FCN (Fully Convolutional Network) is applied to the network structure, which has encoding layers in the former part and decoding layers in the latter part. The encoding layers summarize image features in a receptive field in stages from a narrow area to a wide area by feature extraction using convolution operation of CNN（Convolutional Neural Network）layers and feature shrinkage using pooling layers. The decoding layers expand the encoded features by deconvolutional and unpooling operations and output discriminated labels from predetermined categories through a softmax operation and an argmax operation.

FCN extracts features for every pixel from its receptive field and discriminates its category using the extracted features. A trained model which is consisted of many parameters is obtained by an optimization process that minimize sum of errors from all pixels between the annotation data and segmented image inferenced from the SEM image samples.

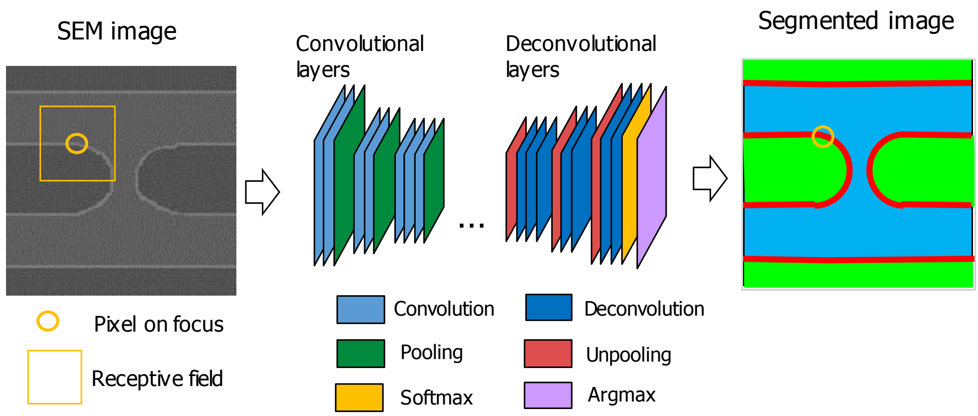

Figure 4. Approximate structure of the contour extraction network.

2.4 Inference process

In the contour extraction process, contours are inferenced from given SEM images using the trained model. Performance of segmentation can be expected high when the given SEM image is similar to any of training samples. Here, positional change in an image could be negligible because FCN has preferable immunity against changes of layouts in an image.

3. EVALUATION EXPERIMENT

Evaluation experiment of the proposed method is described in this section. Experimental conditions, examples of experimental results, quantitative evaluation results and discussion on the experimental results are described.

3.1 Experimental conditions

SEM images of SAQP (Self-Aligned Quadruple Patterning) are used for the experiment. SEM images of this pattern contain two layers. There are combinations of two degrees of pixel size 0.66 and 1.32 nm and four degrees of number of frames 1/2/4/8 for evaluating on different degree of image resolution and SN level. Number of images are 64 for training and 576 for inference in equal proportion to pixel size and number of frames. Each SEM image is divided by 512x512 unit for image wise quantitative evaluation in 3.3. There are set five categories for segmentation: upper contour, lower contour, upper bounded area, lower bounded area and background.

3.2 Examples of experimental results

Examples of segmented images are shown in Figure 5. and 6. with pixel size 1.32 and 0.66, each of which contains outputs with 1/2/4/8 frames. In both figures, manual annotations are shown in 2nd column as ideal outputs. In most parts of the segmented images, contours look very close to ones in the manual annotations, though SN of the SEM images looks fairly low with 1 frame. Here, contours can be extracted using a simple connected components method from pixels with upper and lower contour labels, excluding some erroneous regions.

There are some fragments of false positive errors (contour pixels which exist in the segmented image and not in the manual annotation) near the image boundaries in Figure 5. Some errors near image boundaries are much larger, like a false negative error (contour pixels which exist in the manual annotation and not in the segmented image) in the first row of Figure 7. This type of errors appears because some part of field of view of the deep learning network protrudes outside of an image and performance of segmentation declines. There are also errors when image quality is especially low, like an error in the second row of Figure 7. Most of this type of errors appears with 1 frame, some with 2 frames.

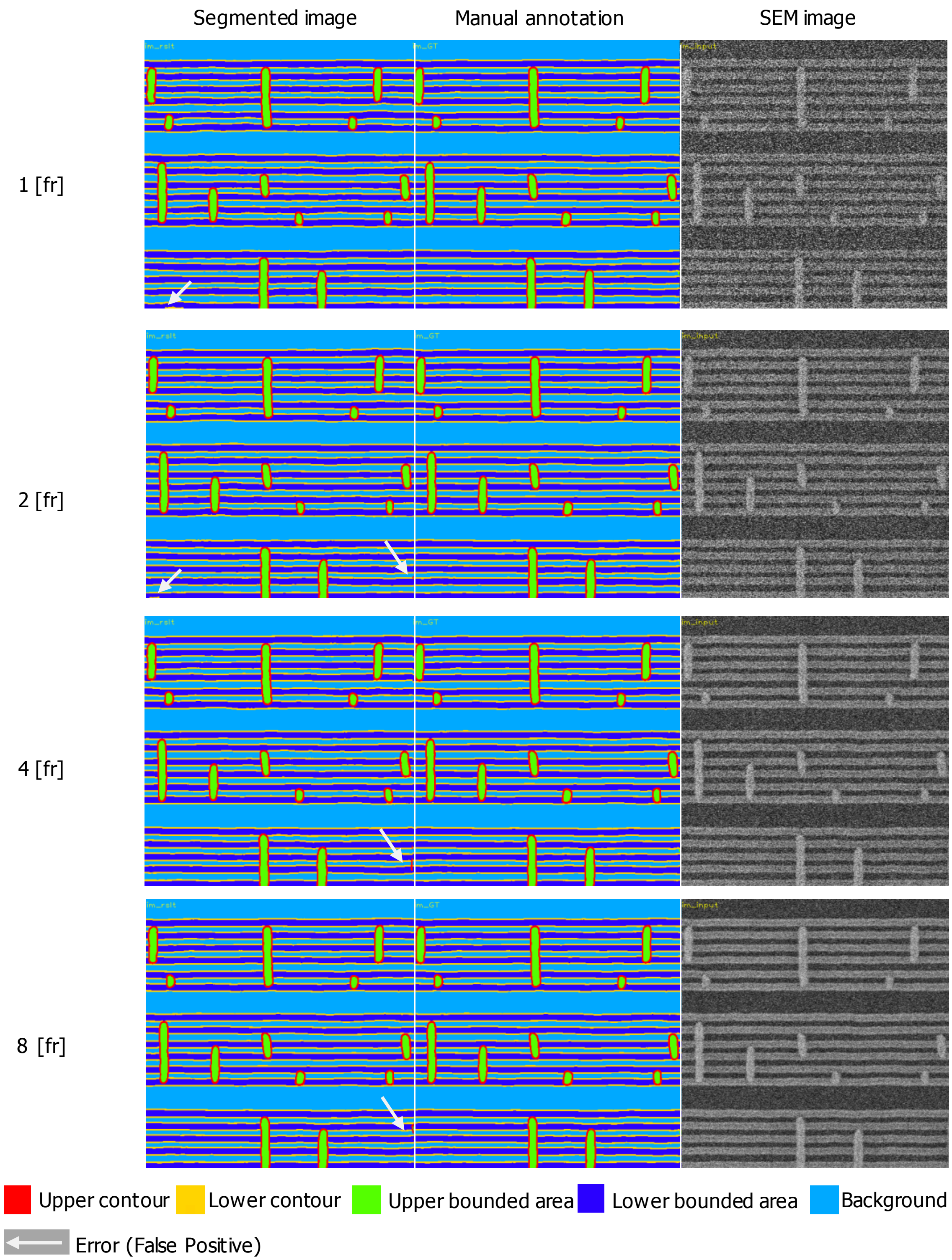

Figure 5. Examples of contour extraction of pixel size 1.32 [nm/pix]

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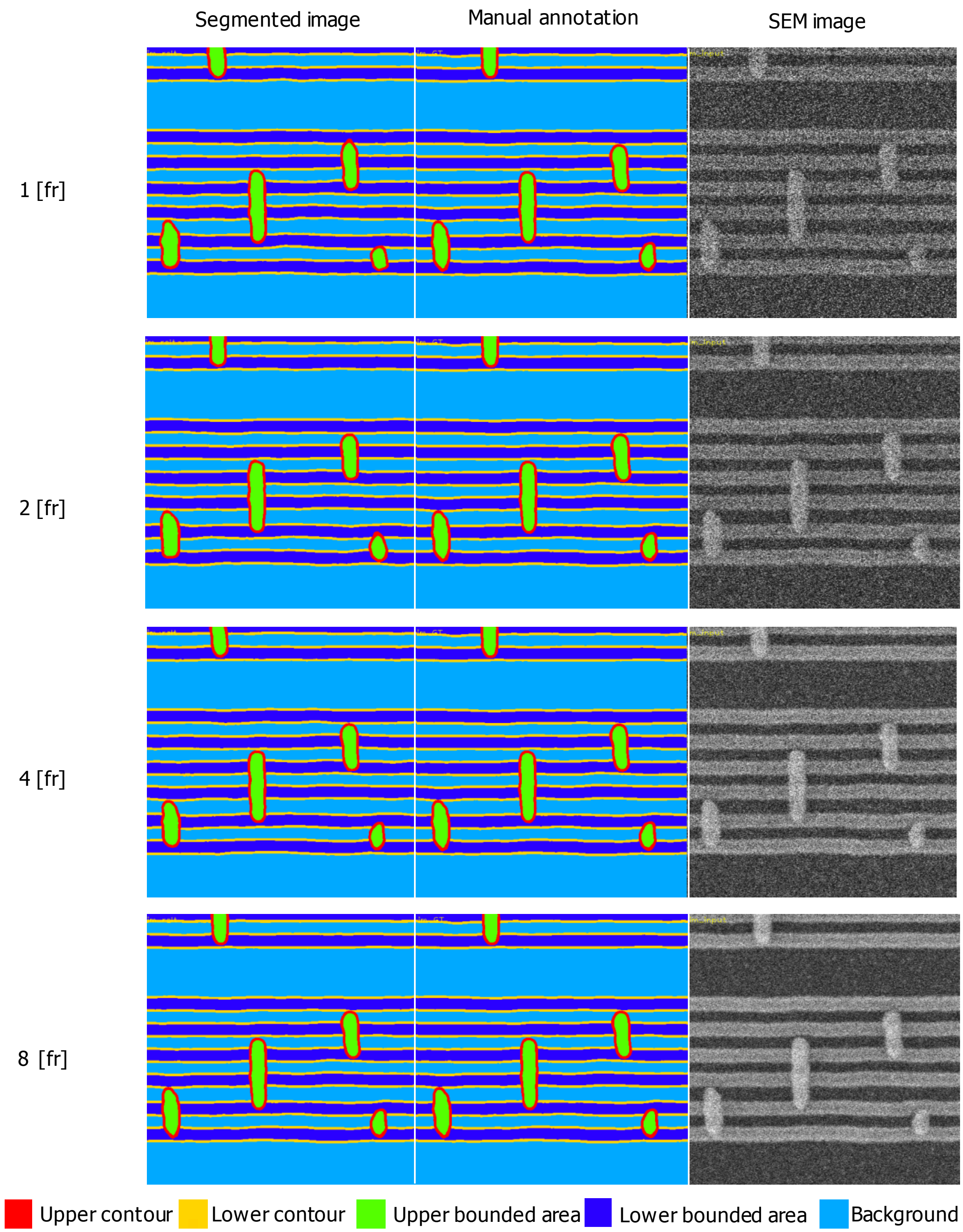

Figure 6. Examples of contour extraction of pixel size 0.66 [nm/pix]

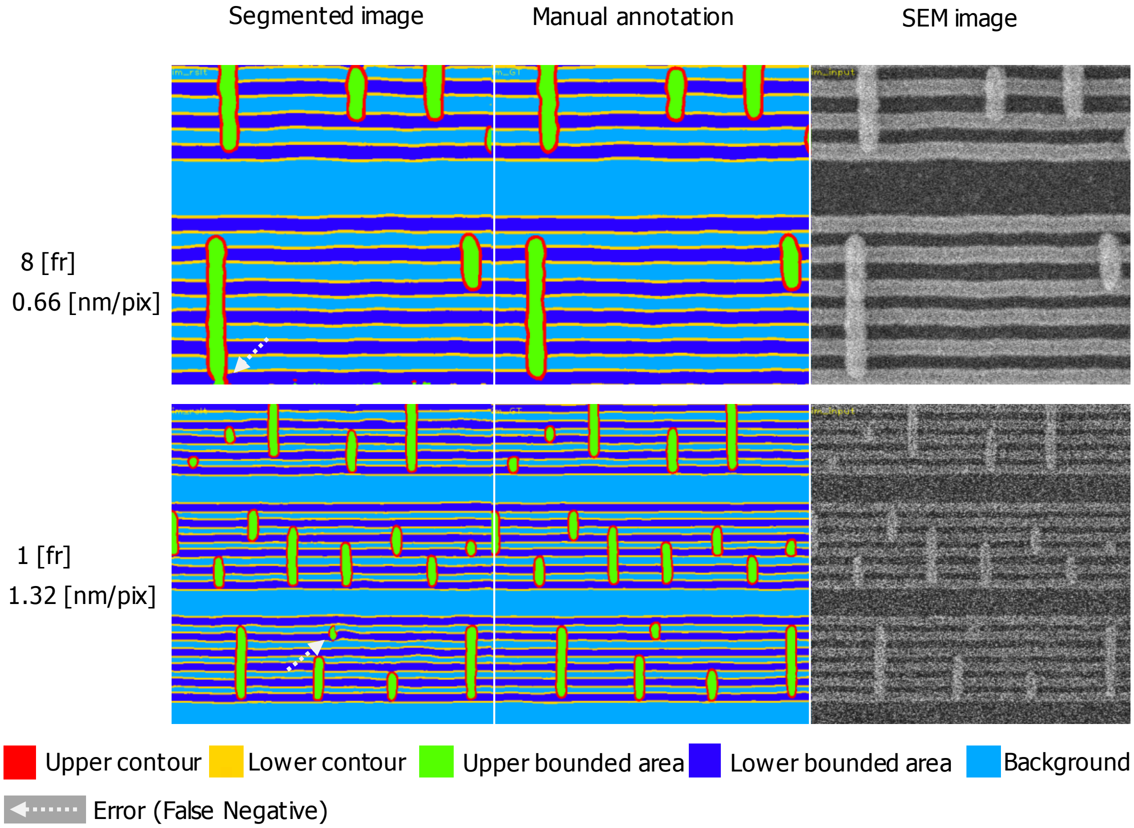

Figure 7. Examples of failure cases.

3.3 Quantitative evaluation result

A quantitative evaluation was done using an evaluation metric named as contour extraction ratio, which evaluates approximate shapes of contours, assuming when they are used for initial contour of DBM named as IBC.

Contour extraction ratio evaluates image-wise contour extraction strictly as follows. First, thinning image processing is done to contours in a segmented image and an annotation datum. Then, each contour in a segmented image is compared manually to corresponding contour in the annotation datum. If there is any false negative concatenated more than 3 pixels or false positive concatenated more than 10 pixels, the contour is NG. If there is any NG contour, the segmented image is NG, otherwise OK. Contour extraction ratio is calculated by percentage of OK to amount of segmented images. In the comparison of contour above, errors in neighborhoods of 10 pixels from image boundaries are diminished as tolerant area where segmentation performance decrease significantly. Distortion of shape is also diminished in the comparison, unless it does not cause any topological disturbance.

Contour extraction ratio calculated from the experimental result is shown in a detailed form in Table 1 and in an aggregated form in Table 2. Though there is monotonic performance decline with decline of number of frames in both tables regardless of pixel size, contour extraction ratio is close to 90% (actual 87.5%) in worst case with 1 frame, with which SN of the SEM images looks fairly low in Figure 5 and 6. There is also performance decline as pixel size decrease in both tables regardless of number of frames. This performance decline comes from errors near image boundary where receptive field of the network protrudes out, and effect of boundary becomes larger with smaller pixel size because there are less texture in the receptive fields.

Table 1. Contour extraction ratio on each condition.

Pixel size [nm/pix]	# of frames	# of SEM images	Contour extraction ratio [%]
0.66	1	72	87.5
0.66	2	72	95.8
0.66	4	72	97.2
0.66	8	72	98.6
1.32	1	72	87.5
1.32	2	72	97.2
1.32	4	72	100.0
1.32	8	72	100.0

Table 2. Contour extraction ratio aggregated.

Pixel size [nm/pix]	# of frames	# of SEM images	Contour extraction ratio [%]
*	1	144	87.5
*	2	144	96.5
*	4	144	98.6
*	8	144	99.3
1.32	*	288	96.2
0.66	*	288	94.8
*	*	576	95.5

3.4 Discussion on experimental results

The capability of contour extraction from low-SN and multi-layered SEM images was confirmed from the experiment results, visually in 3.2 and quantitively in 3.3. We considered that erroneous contours in cases less than 100% in Table 1. and 2. can be covered by second dedicated contour extraction named as MBC when combined afterward, and by SEM image quality improvement with progress of SEM imaging systems from now on.

From experimental results, this method should work well in the following scope. Resolution of images 1.32 nm/pixel or less would be acceptable. For an example, a condition with image size 4096x4096 and field size 4.5 um is acceptable which is equivalent to 1.10 nm/pixel and general for high-speed SEM scanning. Here, performance decline against resolution increase can be overcome by simple image shrinkage. The effect of boundary can be reduced by imaging and inferring in larger size, or imaging in larger size and doing lattice division with adequate margin on image borders considering the receptive field.

4. CONCLUSION

We have proposed a contour extraction method for DBM by applying deep learning, which takes pixel-wise segmentation approach. The proposed method aims to be applied to initial contour extraction of DBM for producing initial guess for second dedicated contour extraction, which possesses integrity with contour shape analysis methods.

Experimental results using imec SAQP pattern with low number of frames shows that this method can handle low-SN SEM images captured by high-speed SEM scanning conditions and multiple-layered SEM images with high performance. We believe that this method could contribute to realize hot spot evaluation and systematic defect evaluation with remarkable performance for EUV lithography and multi-patterning before long.

5. ACKNOWLEDGEMENTS

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