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Deep Learning-based Automated Measurement Method for Cross-sectional SEM Images in Semiconductor Devices

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Feature length extraction in cross-sectional SEM (Scanning Electron Microscope) images of modern semiconductor devices is time consuming and laborious task. In this work, for the first time, automated measurement tool based on deep learning (DL) technology was developed; object detection model for determination of coordinate of each unit pattern and semantic segmentation model for obtaining the coordinate of boundary of each region (mask, substrate, and background). By combining results of these two models, typical features such as width and depth etc. are precisely and immediately extracted. We applied this tool to sample trench patterns and realized two orders faster extraction speed than manual operation.

1. Introduction

Etching process development consists of a repetition of recipe planning, etching fabrication, cross-sectional SEM images measurement, and feature (width, depth, etc.) extraction. When the feature extraction is done manually, the precision of the result depends on operator's skill and it will be time consuming task, typically requiring expert to spend 10–15 minutes per image. In order to address this issue, we have introduced rapidly growing DL technology [1] into feature extraction.

2. Experiment

The sample structure is a trench in Si substrate with SiO_2 mask of L/S hp = 50, 90, and 150 nm. Samples were fabricated by inductively coupled plasma etcher and characterized by SEM (Fig. 1 (a)). Image sizes are 1280 × 960 pixel. Totally 123 samples with various trench shapes were prepared. The five extracted features are (i) mask top width, (ii) mask/substrate interface width, (iii) narrowest substrate width, (iv) mask height, and (v) trench depth (Fig. 1 (d)).

3. Methods

All images were divided into three datasets; 90 for training dataset, 20 for verification dataset, and 13 for test dataset. In order to extract features for each L/S unit pattern separately, we utilized two DL-based image recognition methods, *i.e.* object detection [2] and semantic segmentation [3] as shown in Fig. 1. In a prediction step, by defining a label "*pattern*" for unit L/S pattern, object detection model can identify each *pattern* position as bounding box (Fig. 1 (b)). On the other hand, semantic segmentation model can partition image into different regions associated to different materials (mask, substrate and background) and enables to calculate the contour of region boundaries (Fig. 1 (c)). In an extraction step, by means of each *pattern* position, segmentation and contour belonging to each *pattern* are extracted (Fig. 1 (d)). Required features are easily calculated from the coordinates of the key points on the contour.

4. Results and discussion

Learned models were applied to test samples. The prediction time per image was several seconds. Figure 2 shows the result of the extraction step for one sample (#90nm_28). The extraction time per image was less than a second. The precision of the extracted features (Table 1) are acceptable from a point of view of image resolution (about 1 nm/pixel). Therefore, our tool is about 100 times faster than manual operation and its results are independent of operator's skill.

5. Conclusions

In this work, an automated measurement tool for cross-sectional SEM image was developed and applied to trench patterns. This tool can extract features two orders faster than manual operation. Furthermore, it is expected that this reduction of extraction time can contribute to the rapid process development. Therefore, it is inevitable that an automated tool like this will be used in etching process development.

Table 1. Mean values of manually and automatically extracted features for sample 90nm_28.

	Top width [nm]	Interface width [nm]	Narrowest width [nm]	Mask height [nm]	Trench depth [nm]
manually	75.9	123.0	72.2	79.2	174.8
automatically	78.4	125.2	71.8	78.9	174.3

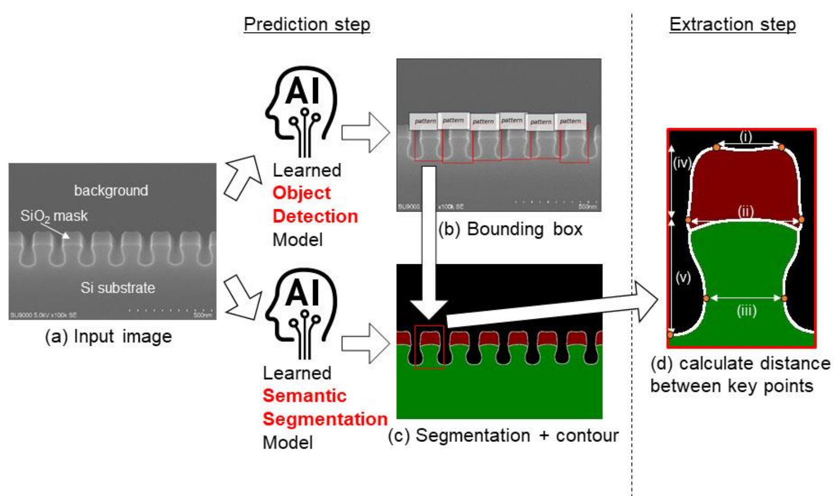

Figure 1. Flow of prediction and extraction steps of automated measurement tool.

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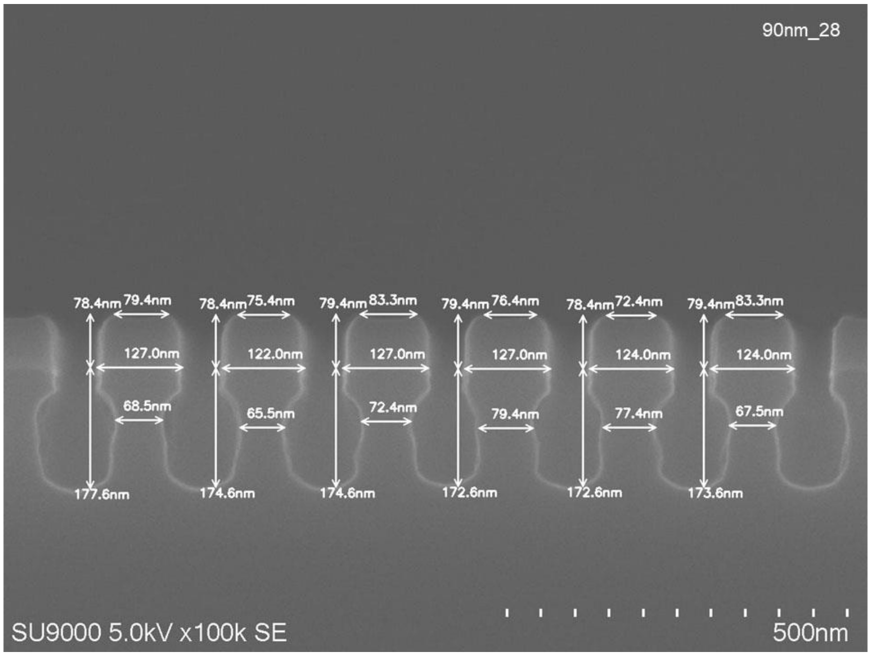

Figure 2. Result of extraction step for L/S hp = 90 nm.

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