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Automated extraction of critical dimension from SEM images with Weave™

Yang Ban[†], Bryan Sundahl[†], Jawad Ahmed[†], Crystal Barrera[*§], S.V. Sreenivasan[*], Roger T. Bonnecaze[†], Meghali J. Chopra[†‡]

[†]SandBox Semiconductor Incorporated, Austin, 9901 Brodie Lane, Suite 160 #568, Austin ,TX 78748

[‡]Meghali.chopra@sandboxsemiconductor.com

[*] University of Texas at Austin, 204 E. Dean Keaton Street, Austin, TX 78712

[§]crbarrera@utexas.edu

ABSTRACT

Current best practices for the extraction of critical dimensions (CDs) from microscopic images requires semiconductor process engineers to analyze images one by one, which is tedious, prone to human bias, time-consuming and expensive. Automated CD extraction using machine learning methodologies is an approach to accelerate and improve the accuracy of this process. Deep learning convolutional neural nets specifically can be used effectively for image segmentation and identification of different material regions; however, providing enough annotated data for training and testing is an ongoing challenge. Here, we demonstrate a method where only one sample image is needed for the neural net to learn how to extract the CDs of interests. The methodology is specifically demonstrated for extracting CDs from a metal assisted chemical etching process. Each experimental SEM image is automatically measured in about 45 seconds. The extracted CD measurements are within 4 nm (<5% error) of the human measured CDs. This automated extraction enables process engineers to improve the accuracy of their metrology workflow, reduce their total metrology costs, and accelerate their process development.

Keywords: Automated SEM analysis, SEM imaging, neural networks, AI

1. INTRODUCTION

Semiconductor process engineers currently spend almost 10% of their time extracting critical dimensions from microscope images. Analyzing images is tedious, prone to human bias, time-consuming and expensive. Also, automation of image analysis is difficult because of various issues with the raw images. These include (Figure 1) effects due to challenges distinguishing foreground and background, damaged structures, effects of irradiation and 3D effects. Extraction of critical dimensions (CDs) from SEM images can be automated to identify edges and materials. Automation of CD measurement from SEM images has the potential to eliminate the tedium of metrology, accelerate data analysis, and free process engineers to spend their time creating and optimizing processes rather than repetitive tasks. Here we demonstrate a successful method based on machine learning to extract the CDs automatically from a series of experimental SEMs.

Image segmentation using deep convolutional neural networks can be found across the literature [1] [2] [3] [4] [5], from such varied fields as digital pathology [4] to computational geology [3]. All current methodologies follow the same pattern: The user is required to possess a large amount of labelled data that is then fed into a training regime that is trained for a large amount of time to produce a network capable of segmenting data. For example, the training of the DeepLabv3 net [1] from Google required 60,000 images and trained for 3.65 days in order to identify 20 different classes of objects. Unfortunately, such a data set does not exist for SEMs of fabricated semiconductor structures, making current strategies unfeasible and when using a net not trained on SEM segmentation, the results can be distressing as seen in Figure 2.

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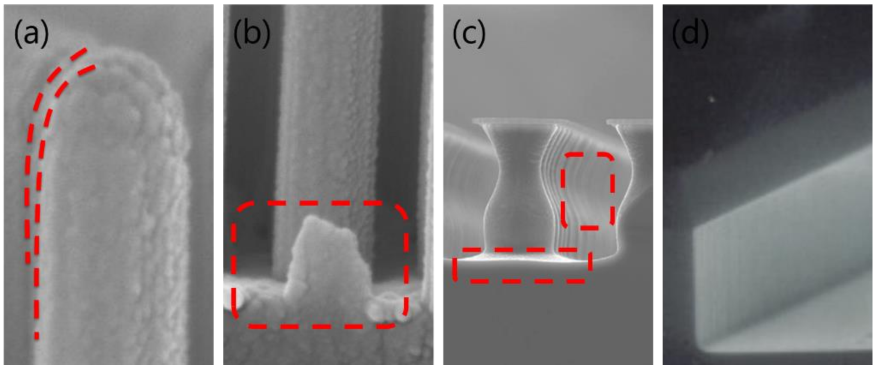

Figure 1. Difficulties involved with analyzing SEM images (a) hard to distinguish between background and foreground, (b) damaged structures, (c) irradiation, and (d) 3D effects.

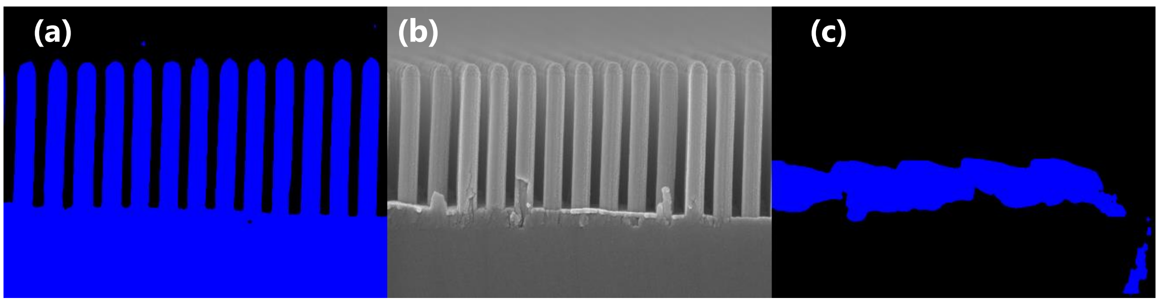

Figure 2. (a) SEM Segmentation with SBS: Weave trained net, (b) the SEM itself, and (c) SEM segmentation with a pretrained DeepLabv3 net.

2. METHODOLOGY AND MODEL CALIBRATION

To demonstrate Weave™ we will use experimental measurements of pillars created by a metal-assisted chemical etching (MACE) process [6] [7]. The MACE process flow is illustrated in Figure 3. A metal catalyst is deposited on resist and the exposed surfaces of silicon. Then during the etching process, the surfaces of silicon in contact with the metal are etched downward with high aspect ratios. The critical dimensions (CDs) for the final structures are the height and width of the resulting pillars. Different etch recipes can be compared by measuring the height and width of each pillar, looking at the uniformity across the pillars. Note that even though there is a metal layer in the stack, each pillar is considered a single material for the purpose of the image processing here.

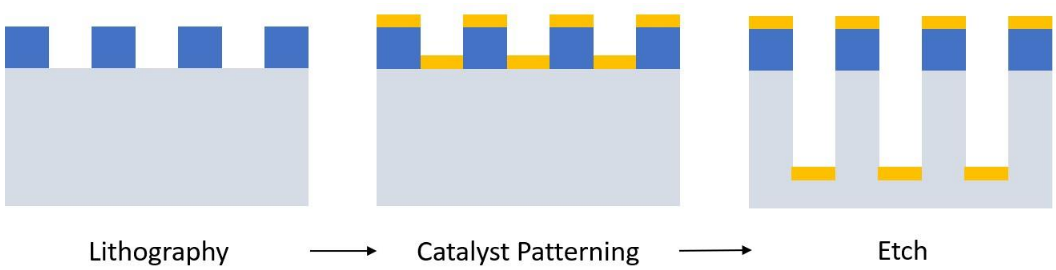

Figure 3. Process flow of the metal-assisted chemical etching process used to generate the pillar structures used in this SandBox Studio: Weave™ study.

The Weave™ AI Engine includes a neural net that has been pretrained for analyzing SEM images. The usual challenge with image processing via machine learning tools is that a lot of data is required to train the net for subsequent reliable CD extraction of specific types of images. The Weave™ AI Engine only needs one SEM image with the CDs to be measured—

but *not* the measurements of the CDs. Weave™ is then tuned based on this single image and automated learning tools within it. The schematic of the Weave™ AI Engine for the user is shown in Figure 4.

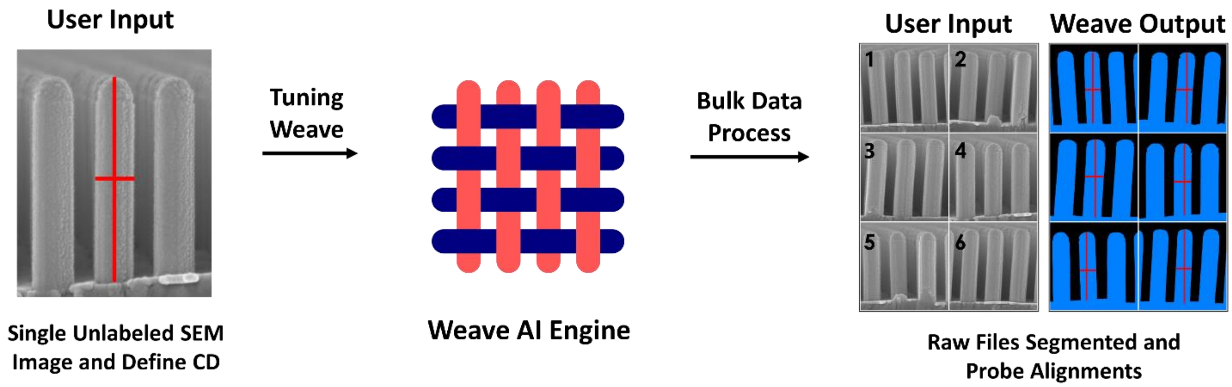

Figure 4. Schematic of Weave™ software process flow. Weave™ requires a single unlabeled image and defined probes to tune the weave AI engine. After the initial tuning, user can automatically process multiple SEM images at once.

Weave™ has the capability to measure many different CDs of interest. These CDs can include material widths and heights (Figure 5 (a) and (b) respectively), vacuum widths and depths (Figure 5 (c) and (d) respectively), as well as contours of either the material or the vacuum (Figure 5 (e) and (f) respectively). Not shown but also available are measurements such as necking, bowing, undercut, sidewall angles, relative heights and widths (heights and widths measured relative to a point of reference, as opposed to at an absolute coordinate), and RIE lag. These CDs will all be measured simultaneously with no additional training or time costs required to add or remove a new CD to the measurement list. Measurements are designated via the drawing of either a line across or a box around the area of the CD area of interest.

3. RESULTS

A single SEM image of pillars from a MACE process was used to tune the Weave™ AI engine. This takes approximately 18 hours. For each SEM image, the Weave™ AI Engine took about 45 seconds to measure both height and width of the center pillar in the image. The results of six separate images are shown in Table 1. In general, the agreement between the actual widths and heights of the pillars measured by a human and the predicted values from Weave™ are excellent. For both CDs, the difference was less than 4 nm. The error in height is less than 1%, and the error in width is less than 5%. These values are accurate enough to reliably evaluate etch recipe performance.

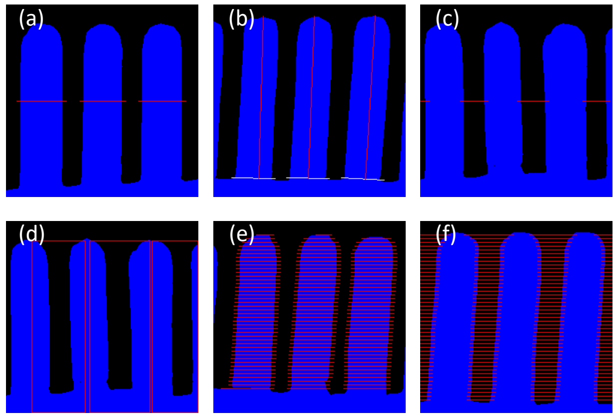

Figure 5. Examples of measurable CDs from SandBox Studio WeaveTM. Red lines mark where a measurement will take place. White lines, when present, denote how the user indicated where a measurement should take place.

Figure 6. An example of overlaid profile red line is etched profile and blue is the target profile.

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Pillar Width			
File #	Actual	Pred.	Error
1	46.2	45.3	1.93%
2	42.6	43.6	2.38%
3	43.7	43.6	0.23%
4	44.0	42.7	2.95%
5	45.4	43.7	3.70%
6	52.0	49.6	4.61%

Pillar Height			
File #	Actual	Pred.	Error
1	203.1	204.0	0.44%
2	202.2	202.0	0.0%
3	204.9	204.1	0.39%
4	204.9	204.0	0.44%
5	202.6	201.3	0.84%
6	206.7	205.8	0.44%

Table 1. Comparison of actual and predicted pillar widths and heights.

CONCLUDING REMARKS

SandBox Studio Weave™ was used to automatically extract CDs of SEM images with no human supervision. Each SEM is fully measured in less than a minutes, and this time is independent of the number of measurements. For 75% of the CDs measured automatically, the error was 2% or less compared to the actual values. The remaining 25% of CDs have errors less than 5%. The accuracy of the method for this example of pillars formed by the metal-assisted chemical etching process is excellent.

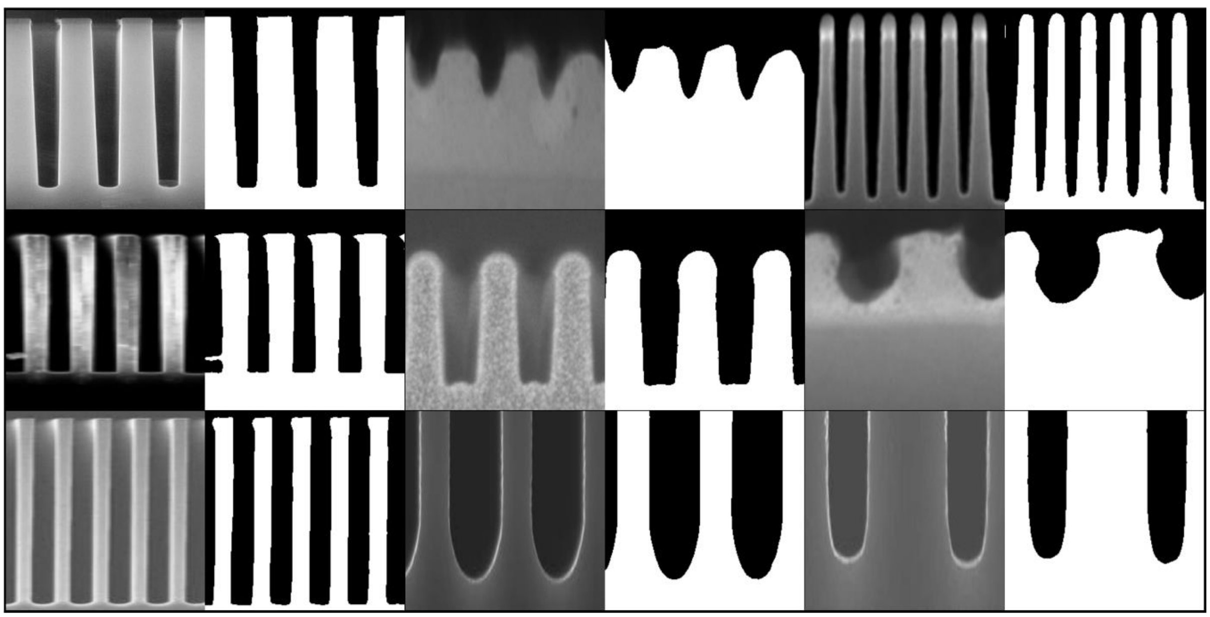

Figure 7. Weave™ AI engine applied in various styles of SEM images.

As noted earlier, a strength of the method presented here is that only a single image is required to tune the Weave™ AI Engine for extraction of specific CDs from a certain type of image. The key to this is of course segmenting the image so that automated measuring tools can be used for measurement of the pixelated images [3]. Figure illustrates examples of raw images and the quality of the segmented images from Weave™. Preliminary results indicate that a variety of nanostructures and SEM quality beyond those examined in this study can also have their CDs extracted accurately and efficiently.

Importantly, this study shows how segmentation of SEM images can be used to characterize SEM images and evaluate recipe performance. Instead of measuring specific locations of critical dimensions of interest inside an SEM image, the segmentation allows users to view the entire profile and compare it with the target profile. Unlike conventional measurements which requires the process engineer to measure a new location whenever new phenomena appear, the segmentation method does not require a user to add or repeat new measurements (Figure 6). Also, the target and a sample profile can be overlaid and can provide an intuitive picture of deviation. This methodology is compatible with new modeling tools such as SandBox Studio™ AI which can use segmented inputs to improve overall model and recipe performance (Figure 8).

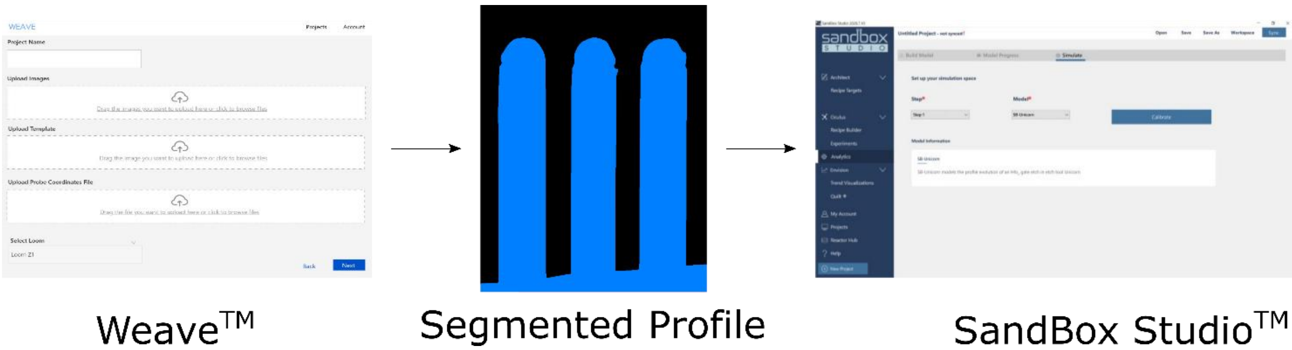

Figure 8. Workflow of recycling segmented image from Weave™ to SandBox Studio^{TM}.

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