

Assessing Scanning Electron Microscopy Stereophotogrammetry Algorithms with Virtual Test Samples

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INTRODUCTION

Planar memory and logic devices have always had functional dependences on in-plane dimensions of their structures, but non-planar devices have added another dependence: on vertical dimensions. For example, the size of the conduction gate channel of a FinFET (a field effect transistor with raised channels, called fins, between source and drain) depends on the height of the fin. Optical and electron microscopy images have only two spatial dimensions—in the lateral plane. Their third dimension is an intensity. However, images from different viewing angles may be combined. Features extended along the insensitive vertical axis in one image will have a component in the sensitive lateral plane in one or more of the others. This permits in principle reconstruction of the 3D shape via stereophotogrammetry. Application of stereophotogrammetry to scanning electron microscopy (SEM) was described by Piazzesi in 1973.¹

Since SEMs now have spatial resolution near 1 nm, the question naturally arises whether SEM-based stereo methods are sufficiently accurate for 3D nanometrology needs. Apart from the usual question of measurement errors that affect the inputs (e.g., the SEM images and the coordinates and angular viewpoints assigned to them) and how these errors then propagate to the result, there is the question to which we here address ourselves: whether important errors result from assumptions and approximations within the reconstruction software itself. For example, reconstruction of the position of a point A on the sample generally requires identifying its corresponding homologous image points A , A' , etc., in two or more different views. Identification may be based on similarity of appearance as determined by correlation, but this is an approximation since appearance changes partly due to electron beam/sample interaction effects for which the reconstruction software does not account. Filtering may also be used to reduce errors caused by noise in the images. Filtering errors will also propagate to some extent into the reconstruction. Because of effects like these, even in the ideal case of error-free inputs, we might expect reconstruction errors. Also, of course, different strategies that might be selected by the algorithm developer to handle these or other issues may differ in their effectiveness.

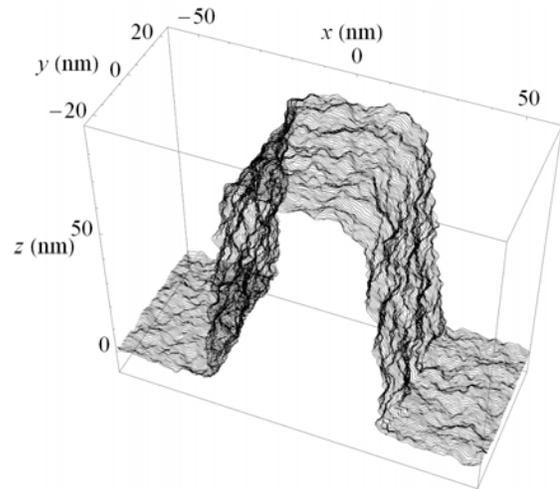


FIGURE 1. Line drawing of the roughest of our 3 virtual samples. The line is oriented to show the right edge. The left edge is obscured by absence of hidden line removal.

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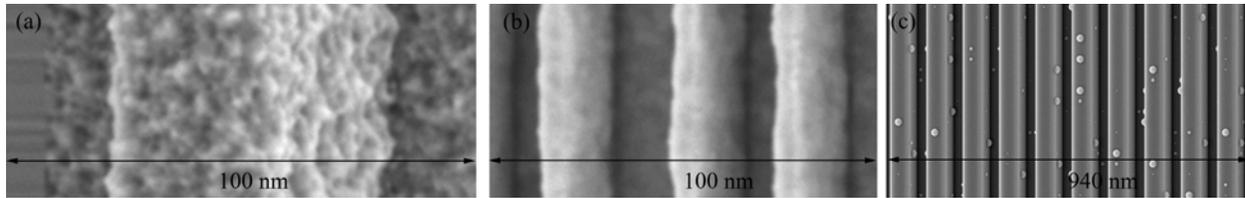


FIGURE 2. Simulated SEM images of 3 virtual samples. The samples were imaged with tilts at 5° increments from -85° to 85° from the normal (axis of rotation along the lines). The views shown here are at 20° .

Developers of most algorithms can test them by applying them to test problems with known answers. We construct such problems by starting with virtual samples. A virtual sample is a mathematical object, which is completely known. The virtual samples are “imaged” at varying tilt angles with an SEM simulator. These images are then input to commercially available stereo SEM reconstruction software, and the software’s output is compared to the known virtual sample to assess errors.

PROCEDURES

We produce images of the virtual samples with the JMONSEL simulator.² The simulator employs models of electron elastic scattering, secondary electron generation, and scattering at boundaries to compute electron yield vs. position, capabilities that have been used for model-based metrology that agrees with transmission electron microscopy and critical dimensions small angle x-ray scattering measurements to better than 1 nm.²

We report results here for three virtual samples with height, h , width at mid-height, w_{mid} , sidewall angle, θ , and top corner radii, r . One was a near-trapezoidal line ($h = 80$ nm, $w_{\text{mid}} = 50$ nm, $\theta = 3^\circ$, $r = 10$ nm) around which a rough skin was wrapped. The sample is shown in Fig. 1 and its image in Fig. 2a. It has 1 nm root mean square (RMS) roughness and a 15 nm correlation length. Some results from this sample were given in an earlier report.³ The second sample (image in Fig. 2b) had the same RMS roughness and similar design but with a longer roughness correlation length (30 nm) and multiple smaller lines ($h = 30$ nm, $w_{\text{mid}} = 10$ nm, $\theta = 2^\circ$, $r = 2$ nm) separated alternately by 18 nm- and 26 nm-wide trenches. The final sample (image in Fig. 2c) was the smoothest. It consisted of an array of 10 lines ($h = 60$ nm, $w_{\text{mid}} = 60$ nm, $\theta = 3^\circ$, $r = 10$ nm) on 100 nm pitch. The sample was decorated with hemispherical bumps on the trench floor, line tops, and line sides.

The images along with the tilt angles are input to the reconstruction software, which produces a number of different outputs, among them a profile across the sample.

RESULTS

Profiles across the middle of the Fig. 2a sample are shown in Fig. 3. The rough black line is the true profile. The smoother green and blue ones were outputs of two commercial software packages. For this very rough structure, the two packages made errors of 1.4 nm or less in the average height and less than 1 nm for the average width. These errors are small enough that we can not confidently attribute them to reconstruction error. They could be due to modeling or sampling errors (the latter because the software did not reconstruct the feature all the way to the edge of the image, so sampled less than the full profile). As we mentioned, the reconstructed profiles are obviously smoother than the true profile. This means the reconstruction is not useful for assessing surface roughness of this sample.

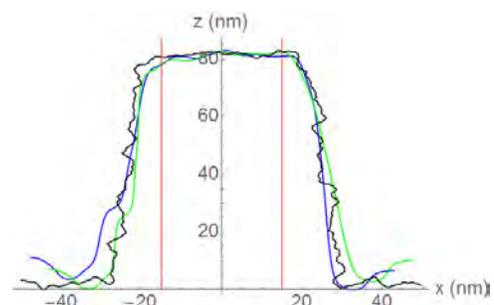


FIGURE 3. Profiles across the Fig. 1 sample from two different commercial software packages (the smoother blue and green lines) superimposed on the true profile (rougher black line).

The Fig. 2a sample was the roughest of the three. At the other extreme, the Fig. 2c sample has line tops and trench floors that are completely flat planes except for a sprinkling of hemispherical bumps. These proved difficult for all

the tested algorithms. Even the best of the reconstructions had the average line almost 40 % shorter than its true 60 nm height, and although the lines are—apart from the hemispherical markers—all the same height, the reconstructed heights varied with standard deviation of more than 8 nm. Interesting in this context is that we could determine the height from the input images along a slice through one of the small hemispheres with much smaller error than this (~1 nm) by using some simple geometry and a calculator. The line shapes in this case were also strongly distorted and about 10 % too narrow. The sample with intermediate roughness (Fig. 2b) also suffered from significant errors on reconstruction, with heights smaller by 4 nm in the wider trench and 8.7 nm in the narrower trench than the true value of 30 nm. On this sample, six pairs of homologous points identified by eye on line tops and in the trenches produced reconstructed heights that averaged only 2.5 nm too low with standard deviation 0.4 nm.

DISCUSSION AND CONCLUSION

Roughness serves a useful function for stereo reconstruction algorithms. It provides a non-periodic surface texture that facilitates identification of homologous points in images from different viewing angles. Two of the samples we examined represent extremes relative to the amount of roughness one would ordinarily encounter in integrated circuit production. The sample of Fig. 1 and Fig. 2a is very rough whereas that of Fig. 2c is very smooth. The best of the tested commercial software algorithms reconstructed the very rough sample with height and width errors of about 1 nm. (This excludes errors due to vibration, noise, angular positioning, etc., for which the reconstruction algorithm bears no responsibility. In a real measurement, these other errors would of course be additional.) Errors on the very smooth sample, on the other hand, were a significant fraction of feature size. The disparate performance at these two extremes motivated a test with a sample (Fig. 2b) intermediate between the two, with roughness bearing a greater resemblance to that expected in practice. Errors in this case were again a significant fraction of feature size, e.g., height errors of 13 % to 29 % of the true height.

Manual line height determinations using simple geometry and homologous points identified by eye outperformed the automated algorithms on the smooth and moderately rough samples. This demonstrates that the larger errors are not *inherent* in these kinds of samples, but must rather be due to less than full use of available information by the tested algorithms. That is, a different algorithm design could perform better. Absence of test problems with known solutions has heretofore been an obstacle to algorithm development. Test problems based on simulated images of samples with known shape can be useful in this respect.

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KEYWORDS

Monte Carlo SEM modeling, nanometer-scale dimensional metrology, scanning electron microscopy, stereophotogrammetry