

Using the Analytical Linescan Model for SEM Metrology

Chris A. Mack^a, Benjamin D. Bunday^b

^aFractilia, 1605 Watchhill Rd, Austin, TX 78703, E-mail: chris@lithoguru.com

^bGLOBALFOUNDRIES (SUNY Poly SEMATECH Assignee), Malta, NY, 12020, USA

Abstract

Measurement of feature roughness is complicated by the confounding noise inherent in SEM images. Edge detection typically requires image filtering to be reliable, but such filtering inevitably alters the roughness that one is trying to measure. Thus, there is a need for an edge detection approach that reliably detects edges in very noisy SEM images without the use of image filtering. The analytical linescan model (ALM) accomplishes this goal by using a physical model for linescan generation to constrain the possible shape of a linescan. Inverting a calibrated model allows edge positions to be estimated with very low sensitivity to noise. The ALM was used to detect edges for the application of roughness measurements and shown to provide superior results compared to conventional methods that employ image filtering.

Subject Terms: CD-SEM metrology, edge detection, line-edge roughness, linewidth roughness, stochastic-induced roughness, LER, LWR

1. Introduction

A critical dimension (CD) scanning electron microscope (SEM) converts a measured linescan into a single dimension number. To better understand how the linescan relates to the actual dimensions of the feature being measured, it is important to understand how the systematic response of the SEM measurement tool to wafer structures impacts the shape of the resulting linescan. Rigorous 3D Monte Carlo simulations of SEM linescans can be extremely valuable for this purpose, but they are often too computationally expensive for day-to-day use. Thus, one approach has been to develop a simplified analytical linescan model (ALM) that is more computationally appropriate to the task of analyzing linescans.^{1,2,3} The ALM is not a first-principles model, but it is inspired by the physics of electron scattering and secondary electron generation, and each term in the model has physical significance. This analytical linescan expression can then be fit to the rigorous Monte Carlo simulations to both validate and calibrate its use.⁴

The general application for the ALM has been the typical forward modeling problem: Given material properties (for the feature and the substrate) and a geometric description of the feature (width, pitch, sidewall angle, top corner rounding, footing), the ALM predicts the linescan that would result. Another interesting application, however, is the reverse modeling problem: given a measured linescan, what feature geometry (at least feature width if not the other geometrical descriptors) would produce that linescan? This reverse modeling problem could be extremely valuable as an edge detection algorithm, especially in the presence of a significant amount of image noise.

One proof of concept for the idea of model-based edge detection has been the use of Monte Carlo simulated linescans in a model-based library look-up scheme.⁵ Monte Carlo simulations populate a library of linescans for a given set of material properties and a wide range of feature geometries. Then, a measured linescan is compared to the library to find the best match (possibly including interpolation). Such an approach has some drawbacks, however, since measurement must necessarily be limited by the range of linescans in the library.

The mathematical details of the ALM have been previously published.^{1,2,3} Here, the ALM will be numerically inverted and fit to a measured linescan in order to detect edges (that is, estimate the feature geometry on the wafer). While such an approach may have wide application for general CD metrology of 1D features, here its use will be limited to one very important application: the measurement of feature roughness. For all results presented below, the software package MetroLER (Fractilia) has been used.

2. Using the Analytical Linescan Model for Edge Detection

The analytical linescan model has two types of input parameters: material-dependent parameters such as forward and backscatter distances, and geometry parameters such as feature width and pitch. For a repeated edge detection application, the material parameters will be fixed and only the geometry parameters will vary. In the simplest case (that is, for simple edge detection), one can assume that only the edge positions for the feature are changing, so that pitch, sidewall angle, corner rounding, etc., are assumed constant. Thus, the use of the ALM for edge detection will involve two steps: calibrating one time the parameters that are assumed to be constant, and then finding the feature edge positions that provide a best fit of the measured linescan to the ALM for each measurement.

Calibration is first accomplished by comparison of the ALM to rigorous Monte Carlo simulations, as has been previously described.^{1,2,3} The goals of this step are to find material parameters over the needed range of applications, and to ensure the fitting is adequate for the needed range of feature geometries. When finished, this calibrated ALM must still be calibrated to the specific SEM images that are to be measured. Since image grayscale values are only proportional to secondary electron signals, at the very least a mapping to grayscale values is required. In real applications, material properties in the experimental measurement will not be identical to those assumed in the Monte Carlo simulations so that some calibration of those parameters may also be required.

Once the ALM has been calibrated to the given SEM image or sets of images, it can then be used to detect edges by inverting the ALM. Due to the non-linear nature of the model, numerical inversion is required using non-linear least-square regression to find the values of the left and right edge positions that best fit the model to the data. Examples of this application will be presented in the next section.

3. Using the Analytical Linescan Model for Measuring Roughness

SEM images of resist features tend to be extremely noisy. High levels of electron dose lead to damage (resist shrinkage), so dose levels (pixel dwell time and frame count) are kept low. This leads to small numbers of detected secondary electrons per pixel and high levels of electron shot noise. The trend to smaller pixel size exacerbates this problem since a constant electron dose per unit area results in a lower dose per pixel as the pixel size shrinks. The problem of precisely measuring the mean CD of a line from a noisy image is mostly solved through averaging. Figure 1 shows an example SEM image for a 36-nm pitch line/space pattern (from Ref. 6). Also shown is one linescan (the grayscale values as a function of x for one y-pixel) and the average linescan (the grayscale values as a function of x after averaging over all y-pixels).

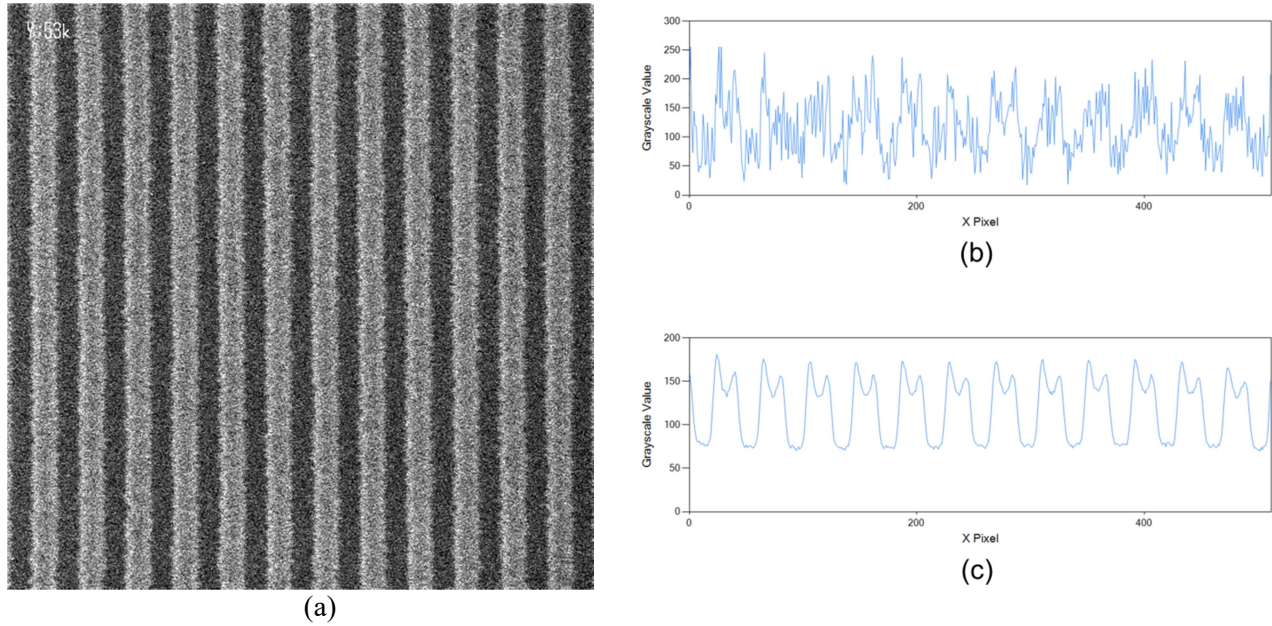
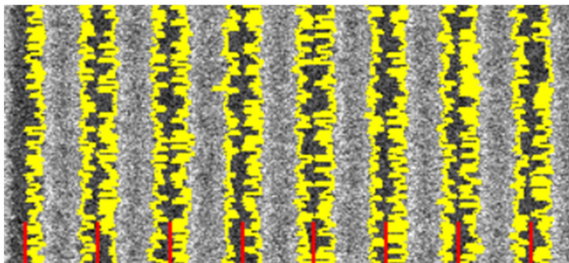


Figure 1. An example SEM image of an EUV exposure of 18 nm lines and spaces: (a) the image, (b) a single linescan at one y-pixel position, and (c) the average linescan, obtained by averaging over all y-pixels. SEM image from Ref. 6.

Edge detection using the average linescan of Figure 1c would obviously be an easy matter (a simple threshold between min and max grayscale values would do). But detecting edges from a single linescan like that from Figure 1b is extremely difficult, a task of pulling a small signal out of a sea of noise. The general solution is to use averaging in the form of an image filter. For example, it is common to use a Gaussian filter of a specific width in the x and y directions (Gaussian sigma is defined as one third of the filter width), though other filters such as median and box (average) are also used. Figure 2 shows the use of a simple threshold edge detection scheme with and without the use of a filter. Without a filter, the edge detection (threshold set to 0.5) is detecting mostly noise and cannot reliably detect the edge position. After applying a 7x2 Gaussian filter (7 pixels wide in x , 2 pixels wide in y), edge detection is fairly reliable.

No Filter



7X2 Gaussian Filter

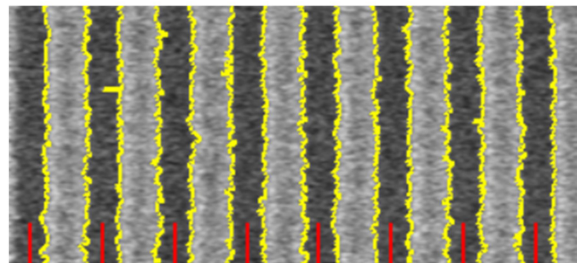


Figure 2. Detecting edges in the SEM image of Figure 1 with and without the use of an image filter.

When SEM images are not very noisy, filtering only in the x -direction (perpendicular to the line edge) is adequate. However, for noisier images (such as the one in Figure 1), averaging in y is also needed. If the goal is to measure the average CD, this is not a serious problem. But when the goal is to measure roughness, one must consider how the filtering affects the roughness measurement. Several authors have shown that filtering affects roughness measurement, especially filtering in the y -direction.^{7,8,9,10} However, if edge detection becomes unreliable without filtering, there may be no choice. The use of any filter reduces the observed roughness, especially at high frequencies but, in fact, at all frequencies.

The ALM as an edge detector allows the detection of edges in a high noise environment without the use of filters. Figure 3 shows the reliable detection of edges for a very noisy image without the use of any filtering. Once edges have been detected, analysis of the edges produces a power spectral density (PSD), height-height correlation function (HHCF), level crossing counts,⁶ or other analysis results. As an example, Figure 4 shows the PSD calculated with and without the use of a Gaussian filter (the ALM is used for edge detection for both cases, so that the only difference is the use of the image filter).

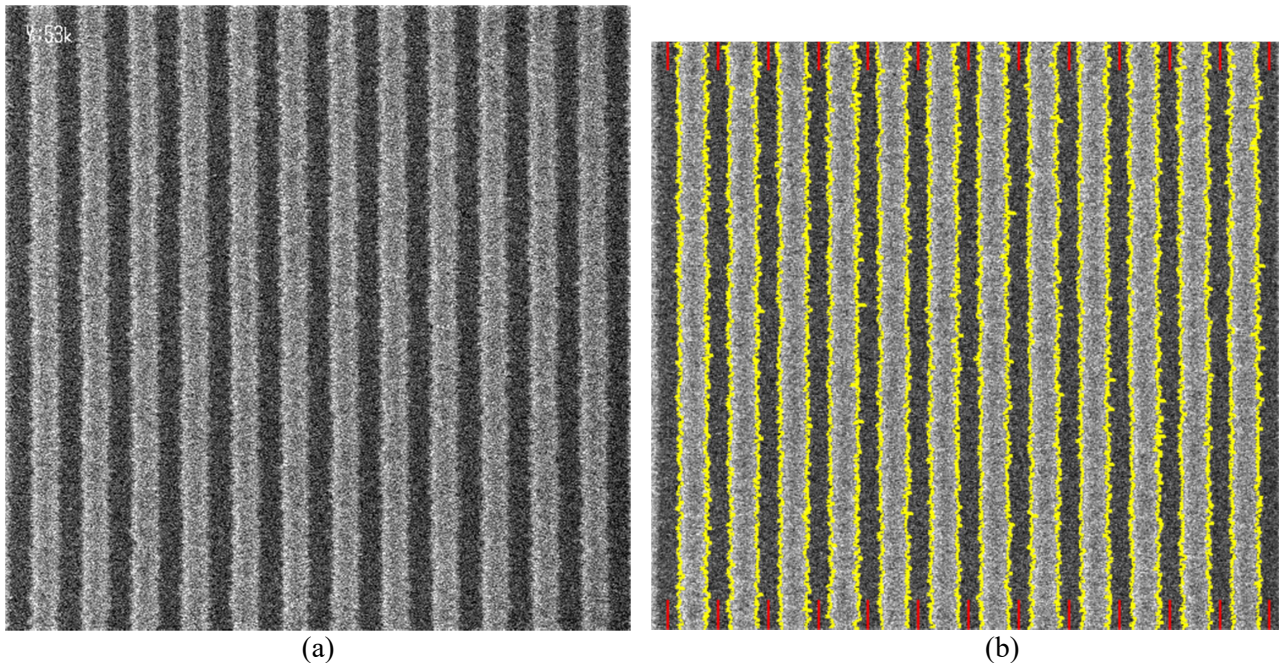


Figure 3. An example SEM image of an EUV exposure of 18 nm lines and spaces: (a) original image, and (b) after edge detection using the ALM (analytical linescan model) with a threshold of 0.5. From Ref. 6.

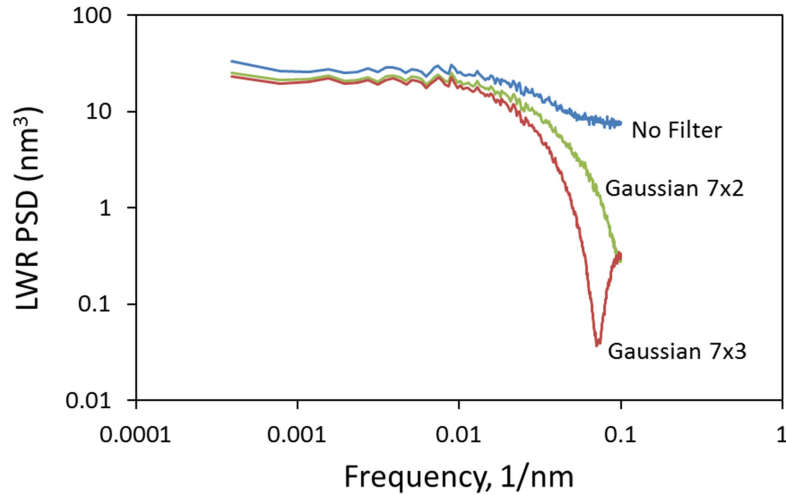


Figure 4. Power spectral densities from many rough features measured using the ALM, with images preprocessed using a 7x2 or 7x3 Gaussian filter, or not filtered at all.

Table 1 shows the measured 3σ LWR as a function of Gaussian filter x- and y-width (in pixels). For each case the ALM edge detection method was used, so that the difference in the resulting LWR is only a function of the image filter parameters. The range is almost a factor of two, showing that many different roughness measurements can be obtained based on the arbitrary choice of filter parameters. In all cases, the ALM edge detection was used. If a conventional threshold edge detection method is used, the range of resulting 3σ roughness values is much greater (Table 2). Similar results are obtained if other filter types (box or median, for example) are used.

Table 1. The raw (biased) 3σ LWR (nm) as a function of Gaussian filter x- and y-width (in pixels), using ALM edge detection.

	y-width = 1	y-width = 2	y-width = 3	y-width = 4
x-width = 1	4.99	4.67	4.03	3.82
x-width = 3	4.92	4.02	3.48	3.28
x-width = 5	4.85	3.82	3.28	3.00
x-width = 7	4.79	3.69	3.13	2.84
x-width = 9	4.73	3.59	3.08	2.80
x-width = 11	4.68	3.54	3.07	2.80

Table 2. The raw (biased) 3σ LWR (nm) as a function of Gaussian filter x- and y-width (in pixels), using conventional threshold edge detection.

	y-width = 1	y-width = 2	y-width = 3	y-width = 4
x-width = 1		11.17	8.52	7.28
x-width = 3	9.58	5.22	4.02	3.72
x-width = 5	8.12	4.62	3.83	3.49
x-width = 7	7.44	4.50	3.78	3.42
x-width = 9	7.03	4.45	3.77	3.41
x-width = 11	6.77	4.44	3.77	3.41

While the arbitrary choice of image filter parameters has a large impact on the measurement of roughness, the impact of threshold value depends on the specific edge detection method used. For the case of a simple threshold edge detection after image filtering, there is one threshold value that minimizes the 3σ roughness measured, with other values changing the roughness quite dramatically (see Figure 5). For the case of the ALM, the choice of threshold has almost no impact on the measured LWR (in Figure 5, the LWR varies from 5.00 nm to 4.95 nm as the threshold is changed from 0.25 to 0.75). Thus, for the conventional method of detecting edges the arbitrary choice of threshold value can cause a large variation in the measured roughness. For the ALM, there are essentially no arbitrary choices that affect the measurement of roughness.

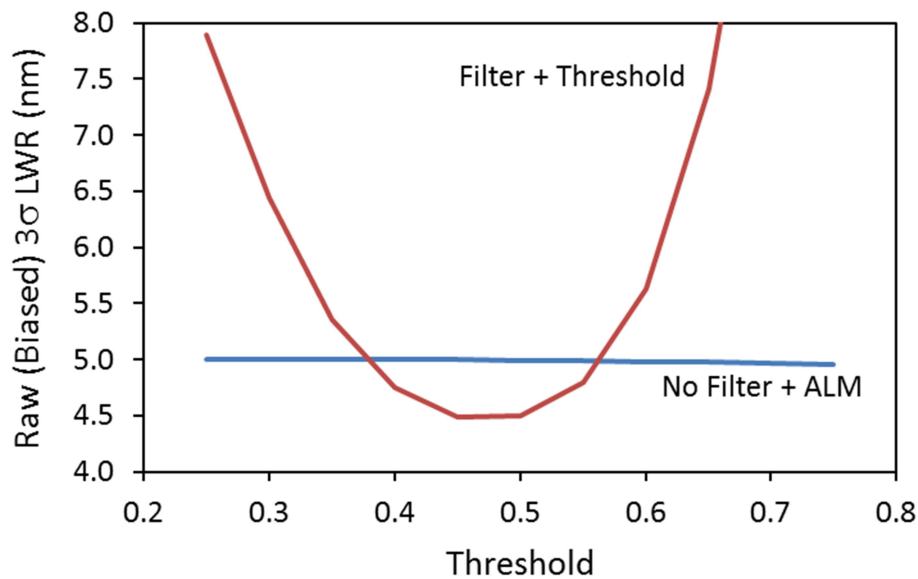
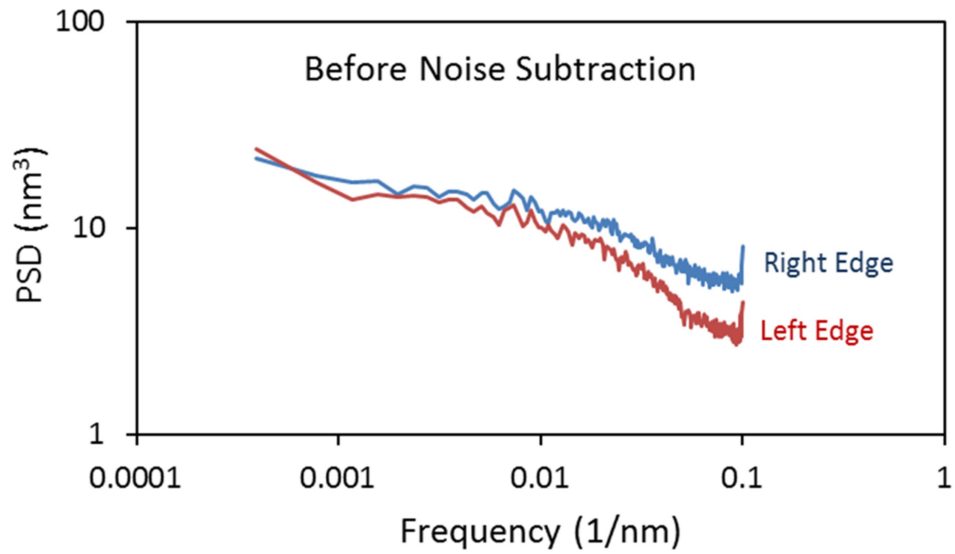


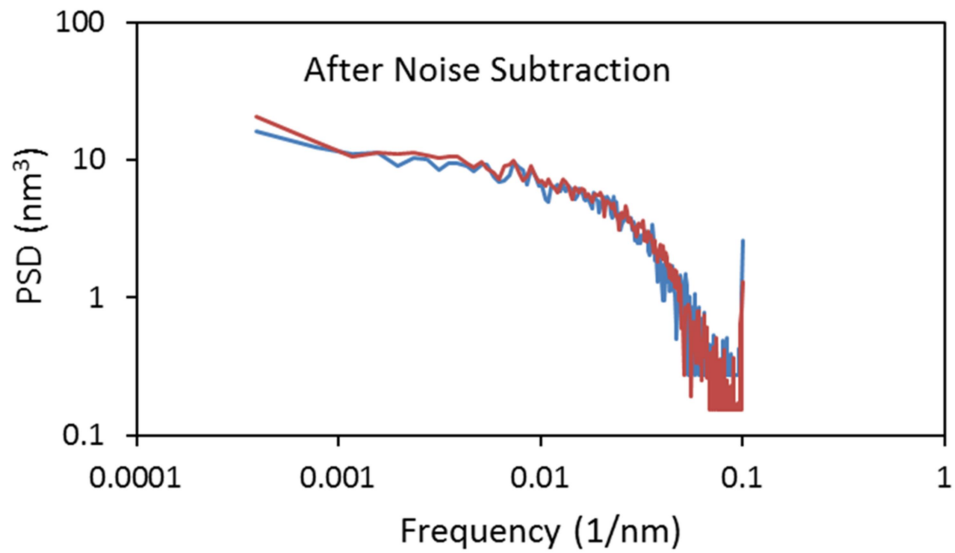
Figure 5. Impact of the choice of threshold value in the measurement of 3σ roughness. For the Filter+Threshold curve, a 7×2 Gaussian image filter was used followed by threshold edge detection. For the ALM case, no image filtering was used.

While the ALM allows accurate detection of edges in the presence of high levels of noise, the noise still adds in quadrature to the measured roughness. For a linescan of a given edge slope, uncertainty in the grayscale values near the line edge translates directly into uncertainty in the edge position. A major difference, though, is that the impact of noise can be measured for the case without filtering. The noise floor of an unfiltered image can be subtracted out from the PSD, producing an unbiased estimate of the PSD (and thus the roughness). For the case of a filtered image, the noise floor is mostly smeared away, so that it cannot be detected, measured, or removed.

Consider the results shown in Figure 6a, where the line-edge roughness (LER) for left and right edges are compared. The raw PSDs indicate that the two edges behave differently. However, these differences are an artifact of the SEM, caused by a scan-direction asymmetry (such as charging) that makes the right linescan slope lower than the left linescan slope. In fact, there is no difference between right and left edge on the wafer.¹¹ By measuring the noise floor for each edge separately, subtracting the noise produces a common left/right LER (Figure 6b) that is an unbiased estimate of the true PSD.



(a)



(b)

Figure 6. LER power spectral densities from many rough features with right and left edges combined separately: (a) raw PSDs after edge detection by the ALM, and (b) PSDs after noise subtraction.

Once the noise has been subtracted, reliable analysis of the PSD or HHCF can lead to reliable estimates of the important roughness parameters, such as the zero-frequency $PSD(0)$, the correlation length ξ , and the roughness exponent H . Of course, the unbiased 3σ roughness can also be obtained. Without removing the noise, extraction of these parameters from the empirical PSD is problematic and prone to systematic errors.

4. Conclusions

The use of the analytical linescan model (ALM) as an edge detection algorithm has been shown to reliably detect edges in noisy SEM images without the use of image filtering. This makes the ALM edge detector ideal for the application of roughness measurement since the filtering commonly used to obtain reliable edges also filters the very roughness that is meant to be measured. The results presented here have shown that the value of 3σ roughness can be changed by a factor of two by an arbitrary choice of filter parameters. Further, the choice of threshold value has almost no impact on roughness measurement using the ALM, but has a considerable impact using the conventional filtered image threshold edge detection. Thus, another somewhat arbitrary choice (threshold value) impacts roughness measurement in the conventional approach, but is unimportant when using the ALM.

While roughness measurement is the first target application of the ALM edge detector, its use in standard CD measurement is also possible. Its robustness in the presence of image noise may make the precision of the edge detection improved over other approaches, though this improvement has yet to be verified.

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