Unbiased Roughness Measurements: Subtracting out SEM Effects, part 3

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Abstract

Background: The measurement of line-edge and linewidth roughness of small features for semiconductor manufacturing is commonly accomplished using a scanning electron microscope (SEM). But these measurements are biased by the noise inherent in SEM imaging.
Aim: Unbiasing of roughness measurements is best accomplished by taking advantage of the frequency characteristics of the noise to measure and subtract it out. This requires the ability to detect edges in a noisy SEM image without the use of standard image filtering techniques.
Approach: A physics-based inverse linescan model is used to robustly detect edges in high-noise SEM images without the use of filtering or image averaging. To validate the efficacy of SEM noise measurement and subtraction, rough features were measured under a wide variety of SEM settings, including number of frames of averaging and voltage.
Results: In all cases, the vast majority of the measurement bias was properly subtracted out. Over a wide range of SEM settings the biased roughness varied by more than a factor of two, but the unbiased linewidth roughness varied by only a few percent.
Conclusions: The approach of inverse-linescan edge detection followed by noise measurement and subtraction leads to reliable estimates of the true (unbiased) line-edge and linewidth roughness of features on the wafer. These unbiased estimates are quite insensitive to metrology tool settings over a reasonable range of values.

Subject Terms: line-edge roughness, linewidth roughness, unbiased roughness, power spectral density, LER, LWR, PSD

1. Introduction

Semiconductor manufacturing today produces feature sizes as small as 20 nm, and at these dimensions every step in the patterning process exhibits stochastic behavior. Photon emission and absorption, and resist exposure, reaction, diffusion, and development can be considered as continuums at larger length scales, but must be thought of as random processes near the molecular level. One consequence of this stochastic behavior is that line edges that ideally should be smooth in fact are printed with nanometer-level roughness. When feature sizes are less than 100 nm, even a few nanometers of roughness along the edge can result in significant problems related to the local variations of linewidth and pattern placement,[1,2] or even catastrophic failures such as broken or bridged features.[3,4]

For these reasons, proper measurement and characterization of stochastic-induced roughness is critical. The most common metrics for roughness are linewidth roughness (LWR, three times the standard deviation of the width of a feature along the length of that feature) and line-edge roughness (LER, three times the standard deviation of an edge relative to its ideal shape along the length of that feature). The most common and most important method for measuring LER and LWR is the top-down critical dimension scanning electron microscope (CD-SEM). Unfortunately, CD-SEM images inherently have measurement noise due to the small number of detected secondary electrons per pixel. This results in a biased

measurement, where the true roughness adds in quadrature with edge detection noise to produce an apparent roughness that overestimates the true roughness. Further, these biases are dependent on the specific CD-SEM tool used and its settings, as well as on the feature being measured and its material and shape.

In our previous studies, a new technique for producing unbiased estimates of roughness parameters was investigated.[5,6] The conventional mode of edge detection in noisy SEM images involves the use of image filtering, which makes edge detection robust but inalterably changes the SEM noise so that it cannot be measured and removed. Thus, unbiasing roughness measurements must be preceded by edge detection on the SEM image without the use of image filtering. An effective approach is to use a physics-based inverse linescan model for edge detection in such a way that edges can be robustly detected without filtering, even for highly noisy images. In this way the SEM noise can be adequately measured and statistically subtracted from the roughness measurement, thus providing unbiased estimates of the roughness parameters. This study will provide more recent results quantifying the effectiveness of this unbiasing procedure.

2. Impact of Noise on Roughness Measurement

SEM images inherently suffer from shot noise, where the number of electrons detected for a given pixel varies randomly and follows something similar to a Poisson distribution. The variance in the number of electrons detected for a given pixel of the image is generally proportional to the number of electrons that impinge on the sample location represented by that pixel, and thus the relative pixel noise in the image goes as one over the square root of the incident electron dose. For some types of samples, electron dose can be increased with few consequences. For many samples, however, high electron dose leads to sample damage (resist line slimming, for example[7]). Generally, electron dose is kept as low as possible, where the lower limit is determined by the impact of SEM noise on the desired measurements. Figure 1 shows portions of three SEM images of nominally the same lithographic features taken at different electron doses.[8]

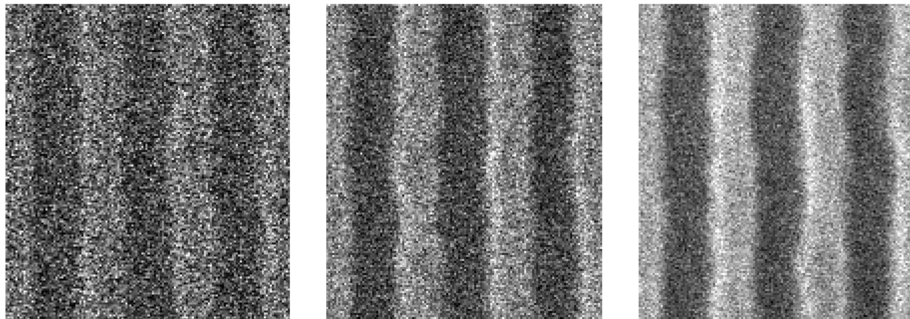


Figure 1. Portions of SEM images of nominally identical resist features with 2, 8, and 32 frames of integration (respectively, from left to right). Doubling the frames of integration doubles the electron dose per pixel. Since the dose is increased by a factor of 4 in each case, the noise goes down by a factor of 2. Figure from Ref. 8.

SEM image noise adds to the actual roughness of the patterns on the wafer to produce a measured roughness that is biased higher:[9]

$$\sigma_{biased}^2 = \sigma_{unbiased}^2 + \sigma_{noise}^2 \quad (1)$$

where σ_{biased} is the roughness measured directly from the SEM image, $\sigma_{unbiased}$ is the unbiased roughness (that is, the true roughness of the wafer features), and σ_{noise} is the random error in detected edge position (or linewidth) due to noise in the SEM imaging and edge detection. Because an unbiased estimate of the feature roughness is desired, the measured roughness must be corrected by subtracting an estimate of the noise term.

Edge detection noise also impacts the power spectral density (PSD) calculated from the measured edge and width variations. Given the grid size along the length of the line (Δy), SEM edge detection noise biases the PSD according to[10]

$$PSD_{biased}(f) = PSD_{unbiased}(f) + \sigma_{noise}^2 \Delta y \tag{2}$$

Since the typical unbiased PSD falls off as a power of the frequency for length scales shorter than the correlation length, the high-frequency biased PSD becomes dominated by image noise (see Figure 2). This insight gives rise to a useful statistical method for noise removal.

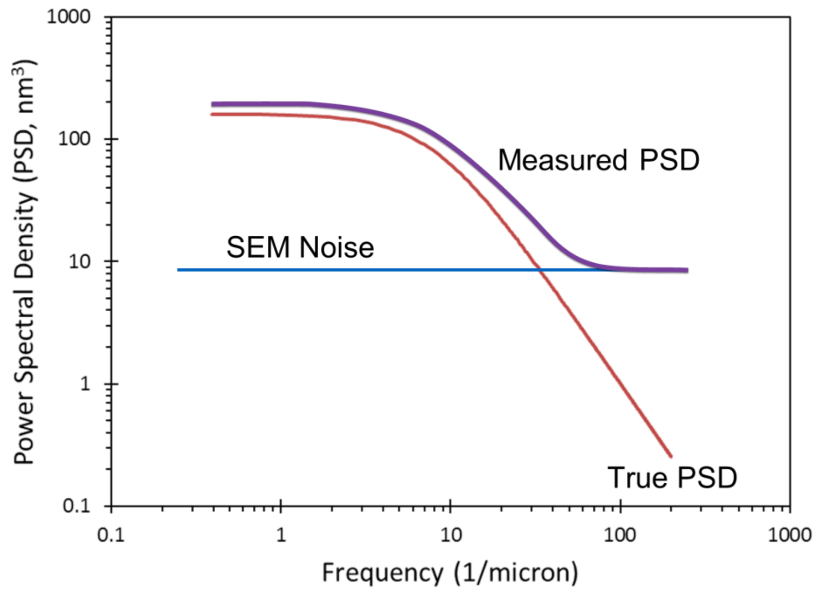


Figure 2. The principle of noise subtraction: using the power spectral density, measure the flat noise floor in the high-frequency portion of the measured PSD, then subtract the white noise to get the true PSD. Figure from Ref. 8.

Consider, for example, a PSD that follows the form

$$PSD_{unbiased}(f) = \frac{2\sigma_{LWR}^2 \xi}{1 + (2\pi f \xi)^2} \tag{3}$$

where σ_{LWR} is the unbiased standard deviation of the linewidth and ξ is the correlation length. (In this case, the roughness exponent is 0.5, typically its lowest value.) The point where the metrology noise exceeds the unbiased PSD will occur at frequencies

$$f > \left(\frac{\sigma_{LWR}}{\sigma_{noise}}\right)\frac{1}{\pi\sqrt{2\xi\Delta y}} \quad (4)$$

To properly measure the noise floor, we would like to have the highest frequency in the PSD (the Nyquist frequency, 1/2Δy) be at least four times the cross-over frequency given by equation (4). This puts a constraint on the SEM pixel size Δy in order to effectively find and measure the noise floor.

$$\Delta y < \frac{\xi}{3}\left(\frac{\sigma_{noise}}{\sigma_{LWR}}\right)^2 \quad (5)$$

For typical images, the metrology noise is about equal to the true LWR so that the maximum preferred *y* pixel size must less than a third of the correlation length. For low-noise images a smaller pixel is required, typically $\Delta y < \xi/6$. A general rule of thumb that Δy must be less than $\xi/5$ is often quoted.

3. Direct Impact of Noise: the number of frames of averaging

The most direct way to change the metrology edge-detection noise (σ_{noise}) is to change the grayscale pixel noise. For a given mean linescan shape, the grayscale pixel noise translates into edge detection uncertainty depending on the slope of the linescan at the feature edge (Figure 3). The grayscale noise can be easily adjusted by changing the number of frames of averaging in the SEM image. Each frame represents one complete scan of the beam across the sample at a very low electron dose. A typical CD-SEM image uses between 8 and 32 frames, where each frame is a complete scan of the beam across the sample once. These frames are then averaged together to produce one final image that is measured. The grayscale pixel noise, and thus the metrology edge detection noise, is expected to go down as one over the square root of the number of frames of averaging.

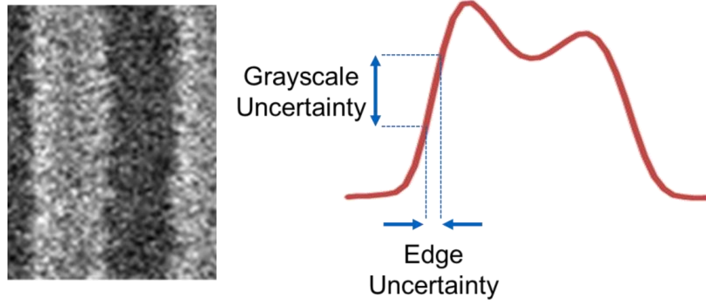
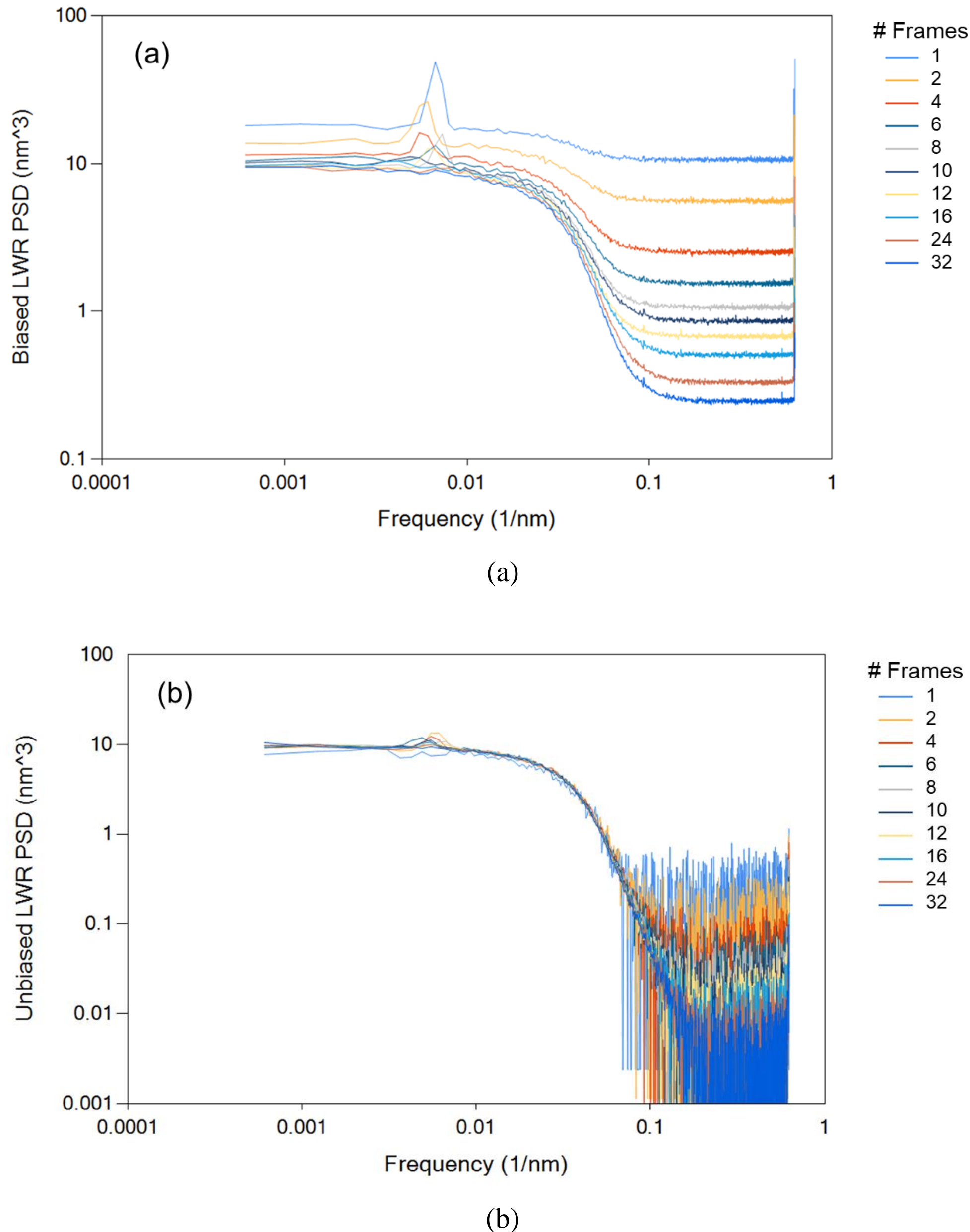


Figure 3. Grayscale uncertainty in each pixel produces detected edge uncertainty depending on the slope of the mean linescan at the line edge.

The experimental study used a Hitachi CG5000 CD-SEM tool. For the first experiment, 32 nm pitch line/space patterns etched into silicon were used. The SEM images were 2048X2048 pixels with a pixel size of 0.8 nm square, 800 V, and 50 images per condition. The number of frames was varied from 1 to 32. The images were analyzed with MetroLER v1.8 using default parameters (no filtering, Fractilia Inverse Linescan Model for edge detection, and a threshold of 0.5). Figure 4(a) shows the biased LWR PSDs that were generated, where clear noise floors can be seen even for the case of 1 frame. Figure 4(b) shows the unbiased PSDs after the SEM noise floor was measured and subtracted out. For 2 – 32 frames, the unbiased PSDs fall

on top of each other, and even the 1 frame case is reasonably similar. Figure 5 compares the biased and unbiased LWR as a function of the number of frames. Comparing 4 frames to 32 frames, the biased LWR changes by 100%, while the unbiased result varies by only 6.7%. Comparing 8 frames to 32 frames, the biased result changes by 50% (1.4 nm), while the unbiased result is different by only 3.5% (0.08 nm). Clearly the act of unbiasing the measured LWR produces a result that is very stable over a wide range of number of frames.

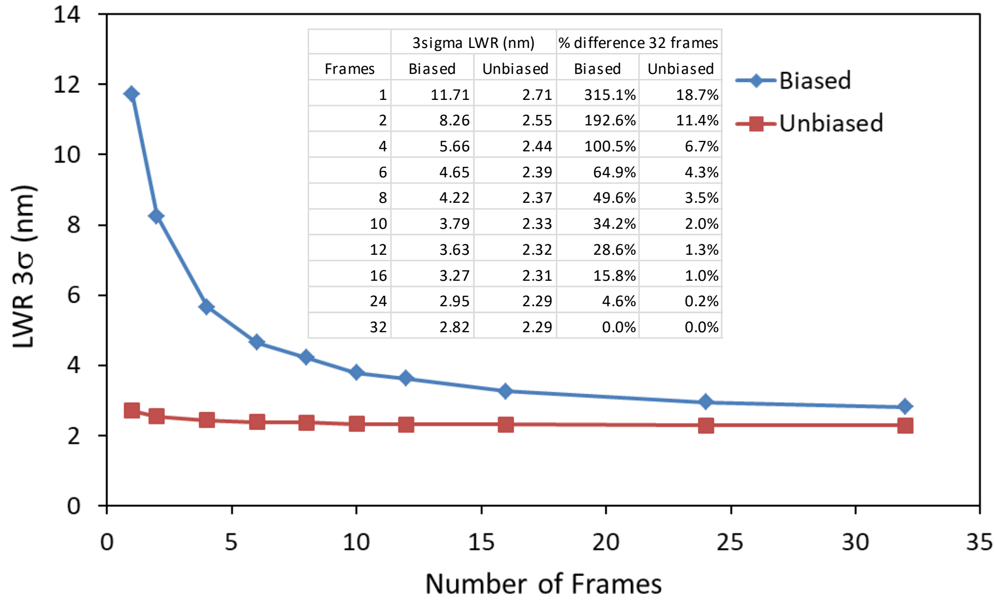


(a)

(b)

Figure 4. Power spectral densities (PSDs) of 18 nm etched lines and spaces where only the number of frames of integration was varied. (a) biased LWR PSDs based on the as-detected features, and (b) unbiased LWR PSDS after measurement and subtraction of the noise floor. SEM conditions: 800 eV, 50 images per condition, 50 features per image, pixel size = 0.8 nm square, image size = 2048×2048 pixels.

Figure 6 shows how the measured noise varies with the number of frames used to capture the image. As expected, the noise varies as one over the square root of the number of frames, at least in the range of 6 to 32 frames. At 4 frames the noise is a bit higher than the expected trend, and at 1 and 2 frames there is a clear deviation from that trend. It is interesting to compare the magnitude of the metrology noise to the unbiased LWR. For 32 frames, the 1σ LWR metrology noise is 0.56 nm while the 1σ unbiased LWR is 0.76 nm. At 16 frames, the noise and signal are roughly equal, while at 4 frames there is more than twice as much noise (1.7 nm) than signal. Yet even for this case the unbiasing works quite well.



	3sigma LWR (nm)		% difference 32 frames	
Frames	Biased	Unbiased	Biased	Unbiased
1	11.71	2.71	315.1%	18.7%
2	8.26	2.55	192.6%	11.4%
4	5.66	2.44	100.5%	6.7%
6	4.65	2.39	64.9%	4.3%
8	4.22	2.37	49.6%	3.5%
10	3.79	2.33	34.2%	2.0%
12	3.63	2.32	28.6%	1.3%
16	3.27	2.31	15.8%	1.0%
24	2.95	2.29	4.6%	0.2%
32	2.82	2.29	0.0%	0.0%

Figure 5. After etch biased and unbiased measurements of 3σ linewidth roughness (LWR) as a function of the number of frames of integration for the data from Figure 4.

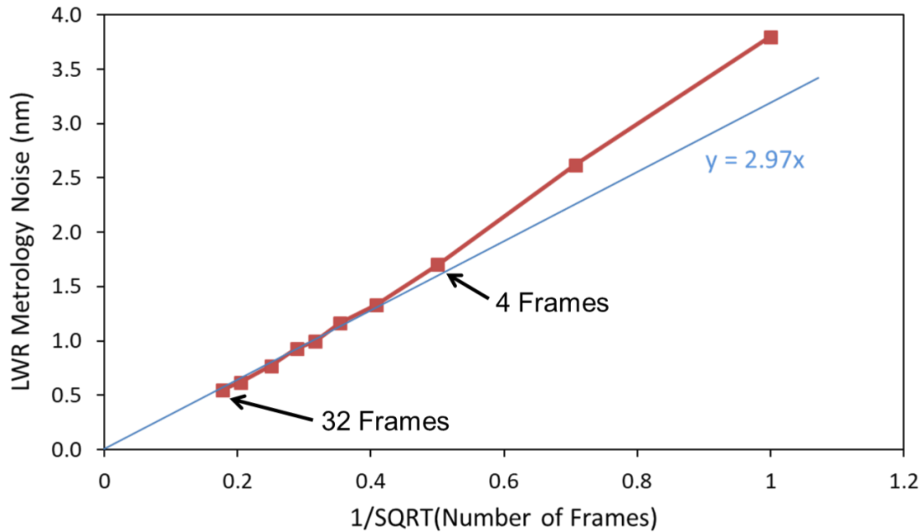


Figure 6. The edge detection metrology noise as measured from the biased PSDs of Figure 4a follows the expected trend for all but the lowest number of frames.

Figure 7 shows similar results for the case of measured resist features. Using 32 nm pitch line/space resist patterns, the SEM images were 2048X2048 pixels with a pixel size of 0.8 nm square, a voltage of 500 V, and 50 images per condition. The number of frames was varied from 2 to 32. For this after-lithography case the residual differences in the unbiased LWR is greater than for after etch, possibly due to resist shrinkage that accompanies measurements at a high number of frames. For example, comparing the 8 frames unbiased LWR result to 32 frames, the after-etch results differed by 3.5% while the after-lithography results differed by about twice as much (7.7%). It is interesting to note that the metrology noise exceeds the unbiased LWR even at 32 frames for this after-lithography measurement dataset.

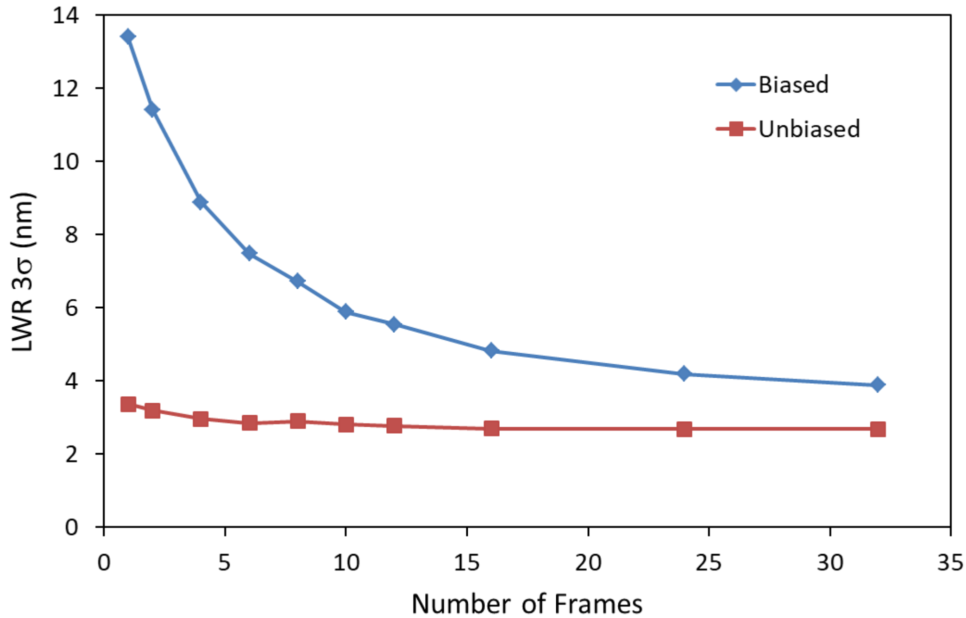


Figure 7. After lithography 32 nm pitch biased and unbiased measurements of 3σ linewidth roughness (LWR) as a function of the number of frames of integration. SEM conditions: 500 eV, 50 images per condition, 50 features per image, pixel size = 0.8 nm square, image size = 2048×2048 pixels.

4. CD-SEM Voltage

SEM voltage has a complicated impact on the measured linescan. Generally, a higher voltage produces a less noisy image, but has the potential for greater sample damage, especially for photoresist. It is common to use 500 V for measuring the roughness of resist lines and 800 V for measuring the roughness of after-etch lines. Since the damage to photoresist lines is less for lower voltages, there is a desire to use 300 V for resist feature measurement.

Here, the voltage on the Hitachi CG5000 CD-SEM was set to 300V, 500V, and 800V to measure photoresist features of nominally 18 nm lines and spaces. Three representative portions of SEM images are shown in Figure 8. Figure 9 compares biased and unbiased LWR as a function of voltage. The unbiased LWR varies by ±3% while the biased LWR varies by 32%. Using unbiased measurements does a good job of removing the impact of voltage on LWR measurements.

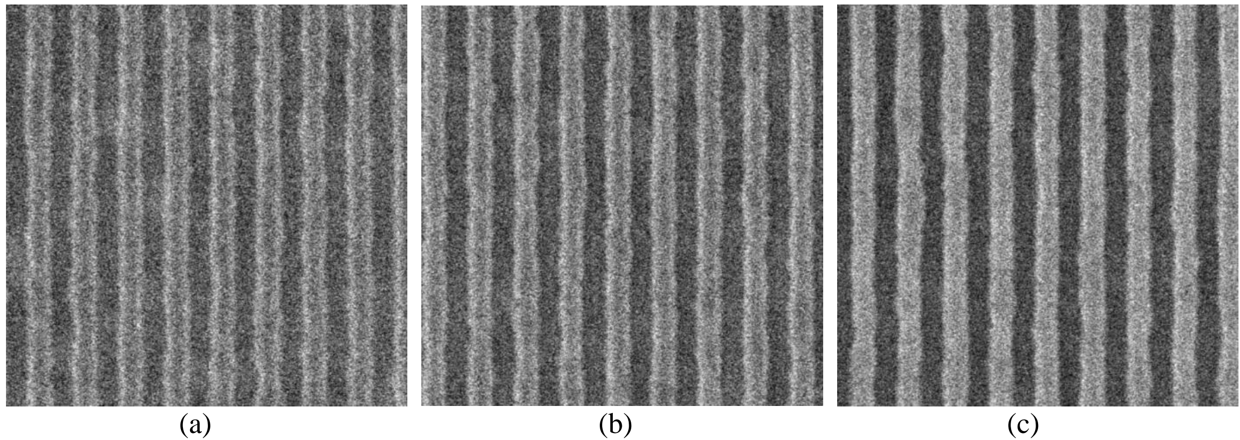


Figure 8. Samples of SEM images of resist 18 nm lines and spaces for (a) 300V, (b) 500V, and (c) 800V operation of the CD-SEM (8 pA current, 16 frames). Figure from Ref. 6.

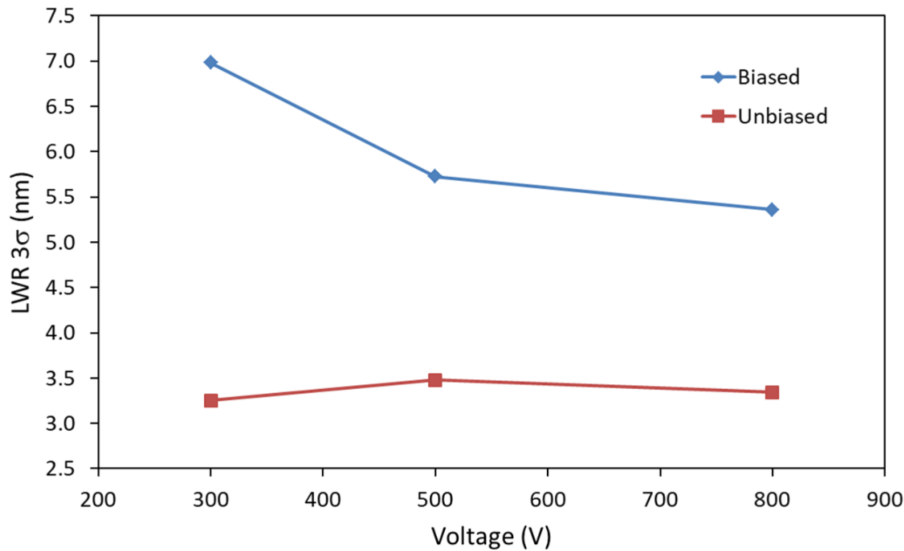


Figure 9. After lithography 36 nm pitch biased and unbiased measurements of 3σ linewidth roughness (LWR) as a function of the number of frames of integration. SEM conditions: 16 frames, 103 images per condition, 45 features per image, pixel size = 0.8 nm square, image size = 2048×2048 pixels.

While the emphasis so far has been on the impact of SEM settings on random metrology noise and its role in biasing LWR measurements, systematic errors in the CD-SEM can also be significant. An important consideration is the variation of SEM imaging characteristics across the SEM image field. As an illustration, Figure 10 looks at how the as-measured (biased) LWR varies across the image field left to right for both 300V and 500V. For the 500 V case there is very little systematic variation across the SEM field except for the last (far right) feature. If this feature were cropped out of the image, there would be no discernable across-field trend. This is in stark contrast with the 300 V case, where there is a systematic 15% rise in the unbiased LWR from the left side of the image to the right. Further investigation confirmed that this LWR variation was caused by a significant left-right variation in metrology noise.

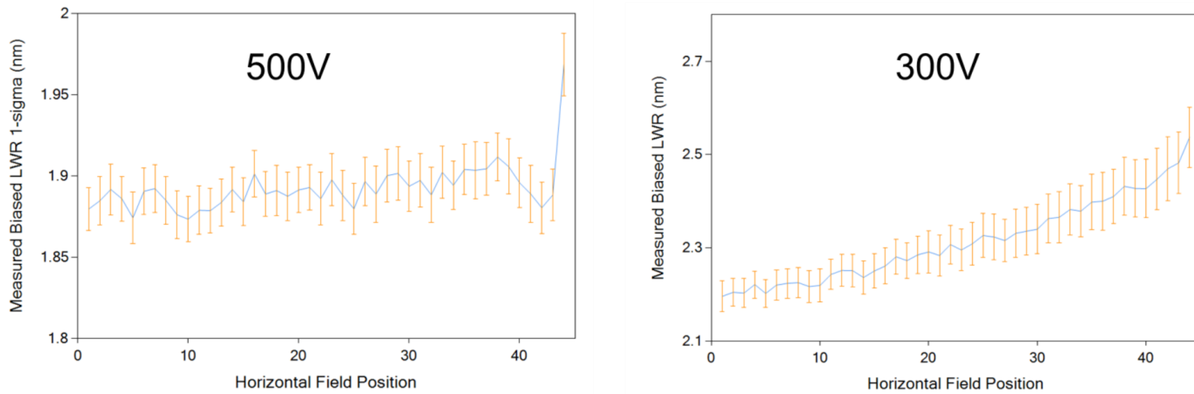


Figure 10. After lithography 36 nm pitch biased measurements of 3σ linewidth roughness (LWR) as a function of position within the SEM image field. SEM conditions: 16 frames, 103 images per condition, 45 features per image, pixel size = 0.8 nm square, image size = 2048×2048 pixels. Error bars show ±2 standard errors (approximately the 95% confidence interval).

5. Conclusions

Taking the SEM out of the SEM measurements requires measuring both random and systematic errors in each SEM image and removing them from the measurement results. Random pixel-to-pixel variations in the grayscale level is an inherent problem for low electron dose images. Since higher dose has implications both for sample damage and for CD-SEM throughput, there is a strong incentive to perform adequate measurements when using images with high noise levels. While difficult for all measurements, high noise is especially troublesome when measuring line-edge and linewidth roughness and related stochastics measures. Edge detection noise adds in quadrature with the unbiased roughness, biasing it higher. It is frequently the case that the metrology noise exceeds the actual roughness on the wafer.

This study and its preceding parts[5,6] have shown that it is possible to accurately measure and remove metrology noise from the biased roughness to produce an unbiased roughness measurement that more accurately reflects the true roughness on the wafer. The first critical step in unbiased roughness measurement is to detect the edges in a noisy SEM image without the aid of image filtering. This is accomplished here using a physics-based inverse linescan model that predicts what features on the wafer gave rise to the measured linescan image data. These detected edges include both the actual wafer roughness and the added noise from the image. Using the power spectral density and the expected differences in frequency response of the wafer roughness and the SEM noise, the noise can be measured and statistically removed from the biased roughness to produce an unbiased roughness, our best estimate of the true feature roughness on the wafer.

CD-SEMs also exhibit systematic errors such as across-field variation. Image distortion (a variation in magnification across the SEM image field) produces an apparent increase in the low-frequency portion of the PSD.[11] Here we have also shown that variation in edge detection noise across the SEM image field can also be significant, at least in some circumstances. To move from measuring what is on the image to measuring what is on the wafer requires measuring and subtracting out as many SEM errors as possible.

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