Unbiased Roughness Measurements from Low Signal-to-Noise Ratio SEM Images

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Abstract

Background: Measuring and subtracting SEM noise from a biased measurement of roughness leads to an unbiased roughness measurement. This unbiasing procedure becomes harder as the noise in the image increases. For low image signal-to-noise ratio (below about 2), unbiased roughness measurement becomes less reliable.
Aim: It is important to understand the mechanism for the sensitivity of unbiased roughness accuracy to linescan signal-to-noise ratio in order to look for ways to improve unbiased roughness measurement for very noisy images.
Approach: Using a combination of mathematical analysis, simulations, and experimental data, the role of pixel size and pitch in the signal-to-noise ratio sensitivity are explored.
Results: All evidence points to the correlation of edge detection noise to true edge position as the cause of the errors in unbiased roughness measurement for very noisy images. For small pitch patterns, changes in feature edge position caused by feature roughness changes the linescan slope, which changes the sensitivity of edge detection to SEM image noise.
Conclusions: Smaller pixel sizes and larger feature sizes are less sensitive to the signal-to-noise ratio effects described here. For any algorithm used to measure unbiased roughness, the impact of linescan signal-to-noise must be carefully assessed.

Keywords: linewidth roughness, LWR, line-edge roughness, LER, stochastics, unbiased roughness, linescan signal-to-noise ratio

I. INTRODUCTION

The control and improvement of leading-edge patterning processes in semiconductor manufacturing requires the accurate and precise measurement of stochastic variations such as line-edge roughness (LER) and linewidth roughness (LWR) for line/space patterns. The critical dimension scanning electron microscope (CD-SEM) is the dominant metrology tool for the measurement of LER and LWR. Unfortunately, such roughness measurements always include the impact of random errors coming from the CD-SEM (SEM image noise that results in edge detection noise), which biases the roughness higher.[1] The standard procedure for determining the unbiased roughness is to first detect feature edges from an unfiltered SEM image or images, calculate the biased power spectral density (PSD) from those edges (averaged for all the features in the image or images), measure the metrology noise floor of the average biased PSD, and statistically subtract this measured metrology noise from the biased roughness to obtain the unbiased roughness.[2-5] The accuracy and precision of this unbiasing procedure is a strong function of the edge detection algorithm, which can have more or less sensitivity to SEM image noise,[6] and many important details of how the noise floor is determined and subtracted.

Recently, the importance of the SEM image linescan signal-to-noise ratio (SNR) to the accurate unbiasing of the LWR has been demonstrated.[7] By studying Fractilia's roughness measurements of 32-nm pitch resist line/space patterns as a function of both resist thickness and number of frames of averaging in the CD-SEM, accurate unbiased roughness was obtained using MetroLER under this variety of conditions so long as the linescan signal-to-noise ratio was above about 2. While SNR above two is quite normal, for some thin resist conditions the SNR can be lower, making unbiased roughness measurement difficult for these cases.[7]

This paper will explore the role of SNR in accurate unbiased roughness measurement in more detail. Using a combination of mathematics, simulation, and experiment, the reasons behind poor unbiased roughness measurement accuracy at low SNR will be investigated and some opportunities for improvement will be suggested.

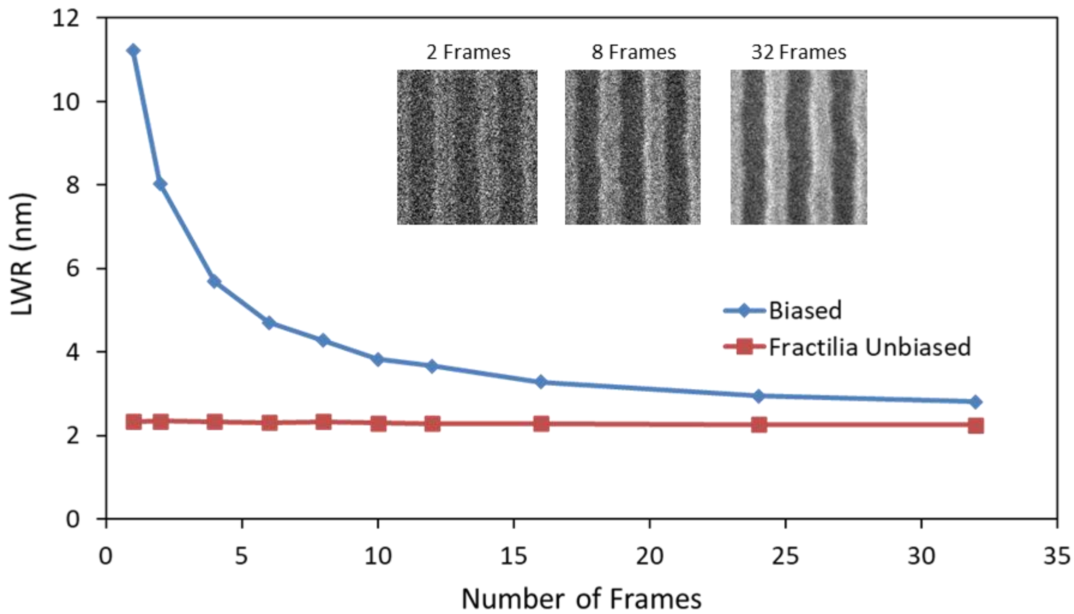
II. VALIDATING UNBIASED ROUGHNESS MEASUREMENTS

One of the most common ways for detecting bias in a measurement is to examine how changes in metrology tool settings affect the mean value of the measurement result. Changes in metrology tool settings can affect both precision and accuracy. Often tool settings are optimized to provide the best possible precision, but the determination of accuracy is notoriously difficult. Bias, however, is easier to detect since it involves detecting simply a change in accuracy. If the mean value of a measurement changes in a statistically significant way as a metrology tool setting is changed, this indicates a *change* in accuracy even if the accuracy itself is not being determined. Since bias is the difference between the mean measured valued and the true value, a change in accuracy indicates the presence of bias.

An unbiased measurement implies an accurate measurement. Unfortunately, standards for evaluating the absolute accuracy of unbiased roughness measurements do not exist. Still, poorly conceived or executed methods for unbiasing the measurement of roughness can be detected by looking for bias in the "unbiased" LER or LWR. Thus, a fairly straightforward way to evaluate the efficacy of an unbiased roughness approach is to change CD-SEM tool settings and determine how much the unbiased roughness results change for a given sample. One hopes that a reasonably wide range of SEM settings would produce the same value (within statical significance) of unbiased roughness.

Prior studies have investigated the algorithms employed by Fractilia's MetroLER stochastics measurement software using the above approach, changing algorithm settings such as threshold[8] and CD-SEM tool settings of pixel size, magnification, voltage, and number of frames of averaging.[5] Of these SEM settings, changing the number of frames of averaging directly changes the noise in the SEM image and is thus the most direct way to evaluate how well an algorithm removes LER/LWR bias caused by SEM noise. Over a range of settings for the number of frames of averaging, the biased roughness can easily change by a factor of 2, but the unbiased roughness should not change. Such experiments, however, are complicated by the potential for sample damage and sample charging: higher frames of averaging produce greater exposure of the sample to electron bombardment, with the possibility that these electrons can modify the sample being measured.

Consider first an after etch inspection (AEI) measurement of biased and unbiased roughness. Using imec's standard process and metrology recipe (800 V and 32 frames of averaging), sample damage is thought to be fairly low. Figure 1 shows the results as a function of the number of frames of averaging varied from 1 – 32. The biased LWR varies by almost 3X over this range (Figure 1a), but the unbiased LWR has just 4% variation (Figure 1b). Perhaps the slight downward trend of the unbiased LWR represents some small amount of sample smoothing due to higher electron dose, since the measured mean CD also decreases by 2.3% over this same range of frames of averaging. In any case, the results show a very adequate job of unbiasing even for very noisy images. Similar results are observed for LER.



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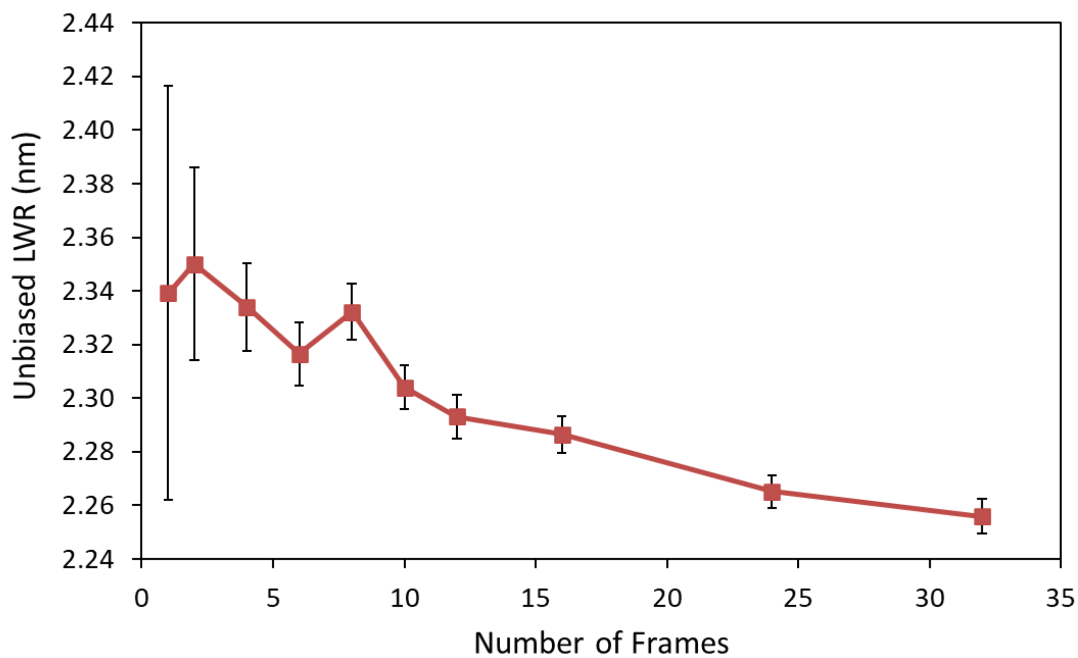
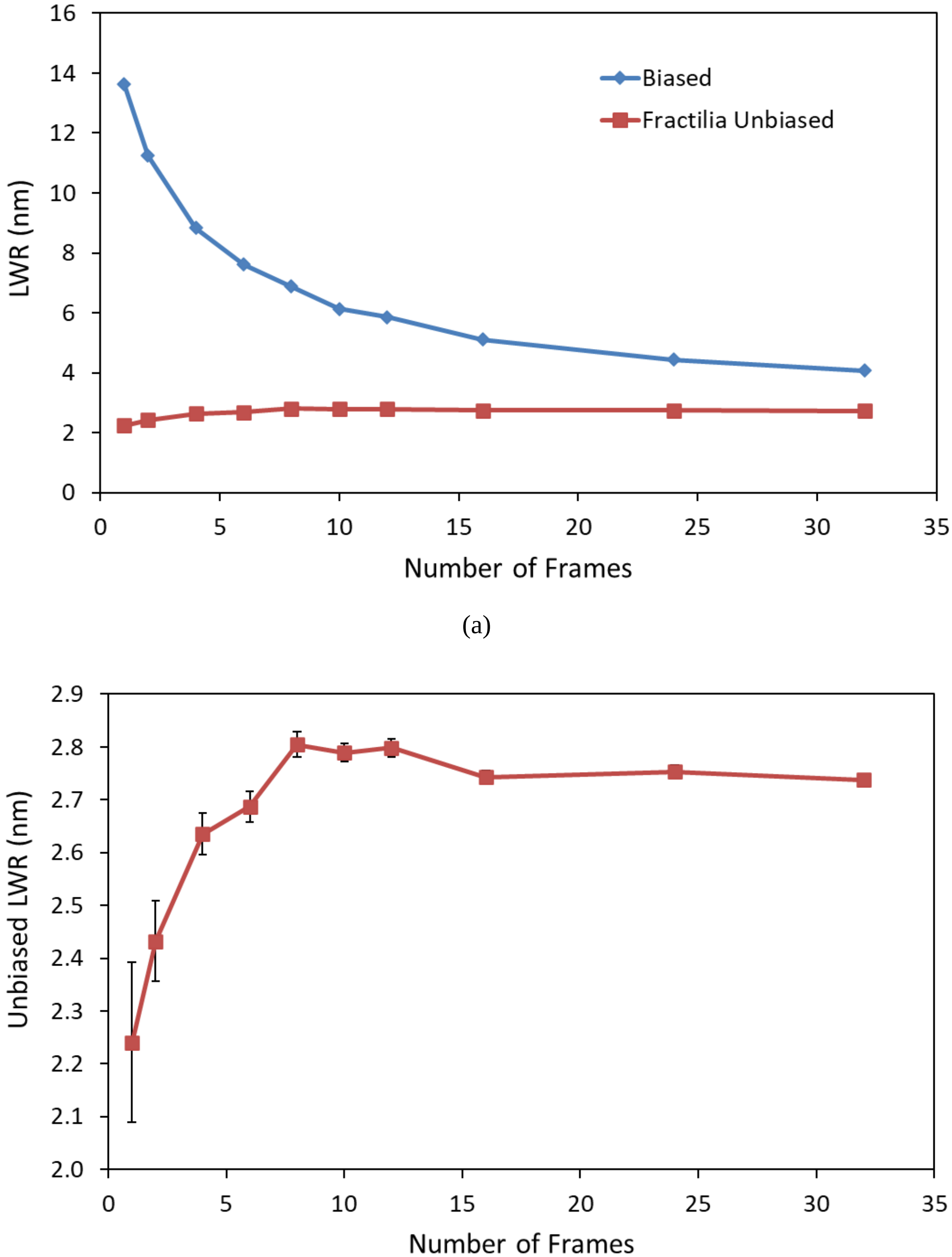


(b)

Figure 1. Roughness measurements as a function of the number of frames of averaging (AEI measurements from Hitachi CG5000, pixel size = 0.8 nm square, image size = 2048x2048, 50 images per condition, equal lines/space patterns with pitch = 36 nm). a) comparing biased and unbiased LWR, and b) a closer view of the unbiased results showing 4% variation across number of frames. Error bars represent ± two standard errors. All images were from Ref. 5 and measurements were performed using MetroLER v3.0.0.



(a)

(b)

Figure 2. Roughness measurements as a function of the number of frames of averaging (ADI measurements from Hitachi CG5000, pixel size = 0.8 nm square, image size = 2048x2048, 50 images per condition, equal lines/space patterns with pitch = 36 nm). a) comparing biased and unbiased LWR, and b) a closer view of the unbiased results. Error bars represent ± two standard errors. All images were from Ref. 5 and measurements were performed using MetroLER v3.0.0.

The after develop inspect (ADI) case shows a different behavior (Figure 2). Like the AEI data, the biased LWR for the ADI data varies significant, but the unbiasing is only fully successful down to 8 frames of averaging. At 6 frames of averaging and below the unbiased LWR begins to fall off, decreasing by 20% down to 1 frame. It is this loss of unbiasing fidelity at low frames of averaging that is the subject of this paper. Note that over this range of # frames, the resist linewidth shrinks by 20%, from 19.3 nm to 15.7 nm.

The loss of good unbiasing performance at low frames of averaging is better expressed as function of linescan signal-to-noise ratio (SNR). This metric begins with the average linescan (see inset of Figure 3), the grayscale value as a function of x-pixel position where each grayscale value is the average of the vertical column of pixels at that x-pixel position (lines and spaces are oriented vertically). From the average linescan for each line feature, the grayscale range is determined (maximum – minimum for both left and right sides, then use the largest of the two). The noise is expressed as one standard deviation of a column of pixels near the center of the space. Finally, the SNR is the linescan grayscale range divided by the 1σ grayscale noise. As a reference point, a linescan SNR of 2 would mean that the average linescan grayscale range was equal to the ±1σ range of grayscale noise, indicating a very noise image. Figure 3 shows the variation of linescan SNR as a function of number of frames of averaging for the ADI data of Figure 2.

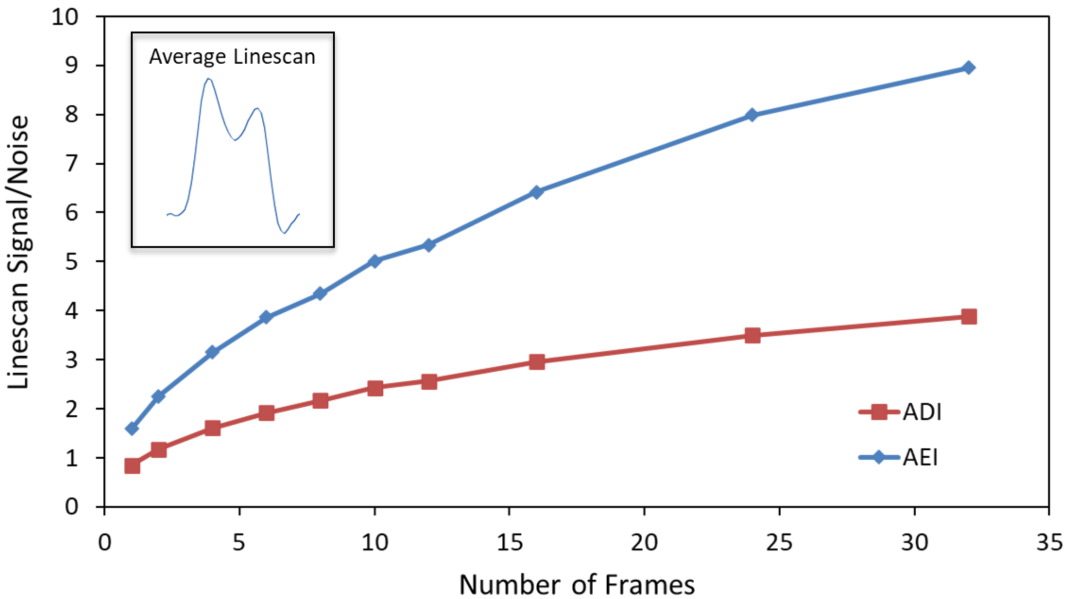


Figure 3. Linescan signal-to-noise ratio tracks with the number of frames of averaging, in this case for the AEI and ADI data from Figures 1 and 2.

Reevaluating the ADI data of Figure 2 in terms of SNR, 6 frames of averaging corresponds to an SNR just below 2, so that good unbiased results are obtained down to an SNR of about 2, then the unbiased LWR falls off for lower SNR. This is the same finding as reported in Ref. 7 across different resist thicknesses and different underlayers. Thus, a simple heuristic guideline has been developed: For SNR greater than 2, the Fractilia approach to unbiased LER/LWR provides reliable results. For ADI data with an SNR below 2, the LER/LWR drops as the SNR gets lower (as much as 20% for SNR below 1) and is thus less reliable.

III. USING SIMULATIONS TO UNDERSTAND THE ROLE OF SNR

Synthetic SEM images can be a useful tool for testing various SEM image-based metrology algorithms for measuring roughness since it is possible to create synthetic SEM images from features with known roughness characteristics.[9,10] The key to their usefulness for any given task, however, depends on how accurately the synthetic SEM images model the phenomenon of interest. MetroLER has the ability to generate synthetic SEM images of line/space patterns using the Analytical Linescan Model[11,12] as calibrated to rigorous Monte Carlo simulations for resist patterns. These synthetic SEM images also include a non-Gaussian noise model and scaling of grayscale values as a function of the amount of noise, mimicking quite closely the behavior observed in commercial CD-SEM tools.[10] A question then arises, can the synthetic SEM images generated by MetroLER reproduce the observed SNR behavior seen experimentally when measured by MetroLER?

The results shown in Figure 4 clearly indicate that the answer is yes. Like the experimental data, the 36-nm pitch synthetic SEM images analyzed in the same way produced the expected unbiased result when the SNR was above about 2, then started to fall off at lower SNR (SNR was modulated by adding more grayscale noise to the images). Thus, it appears that the Analytical Linescan Model (ALM) behind these synthetic SEM images is capturing the relevant effects. It is important to note that ALM does not include resist shrinkage or charging effects. So while these sample modification phenomenon may exist in the experimental data, they are not necessary to explain the observed SNR effect.

An interesting observation from the simulations is that a smaller pixel size enables accurate unbiased roughness measurement at lower SNR. Cutting the pixel size by a factor of two allowed the unbiased roughness to be measured well with 25% lower SNR. A second set of simulations explored the impact of CD and pitch on the SNR effect. Figure 5 shows that larger line and space widths exhibited reduced SNR dependency. In fact, as the pitch becomes large enough so that each edge becomes approximately isolated, there is almost no impact of SNR on the unbiased roughness even as the SNR approaches 1. From this result, it is easy to suppose that the interaction of edges in the SEM (across the line and across the space) are responsible for the SNR dependency of unbiased LER. This idea will be explored in the next section.

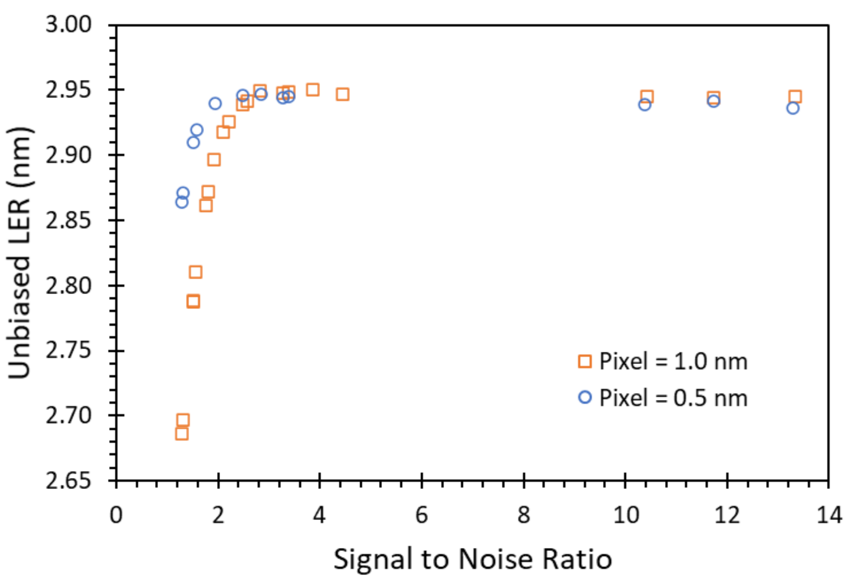
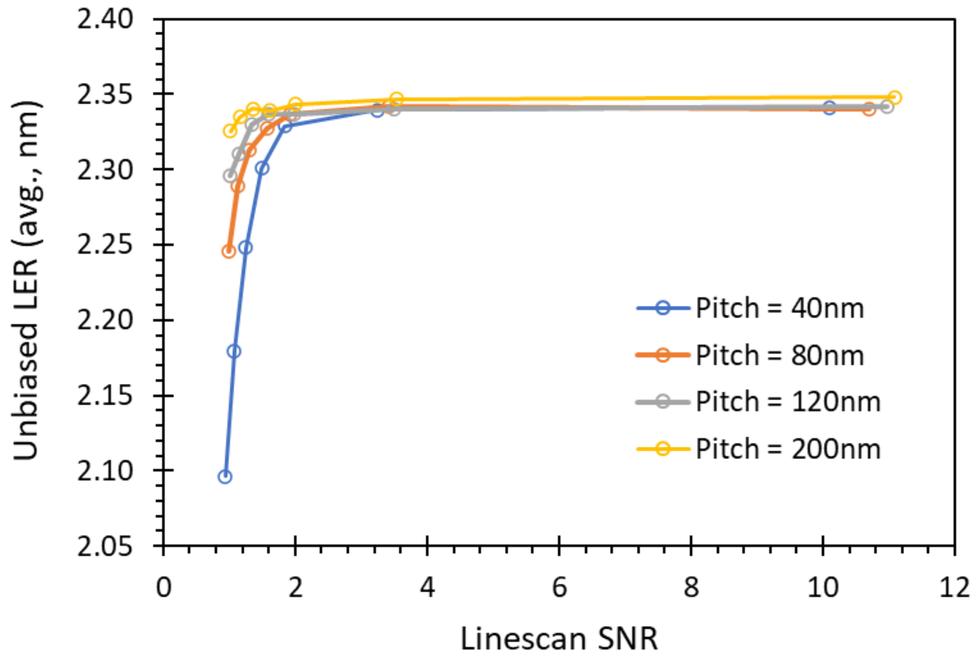


Figure 4. Measurements of synthetic SEM images show the same SNR dependency observed with experimental ADI images. Synthetic images generated by MetroLER for 36-nm pitch equal line/space patterns with an input edge roughness of 3.0 nm (correlation length = 7nm, roughness exponent = 0.7, feature length = 1024nm).



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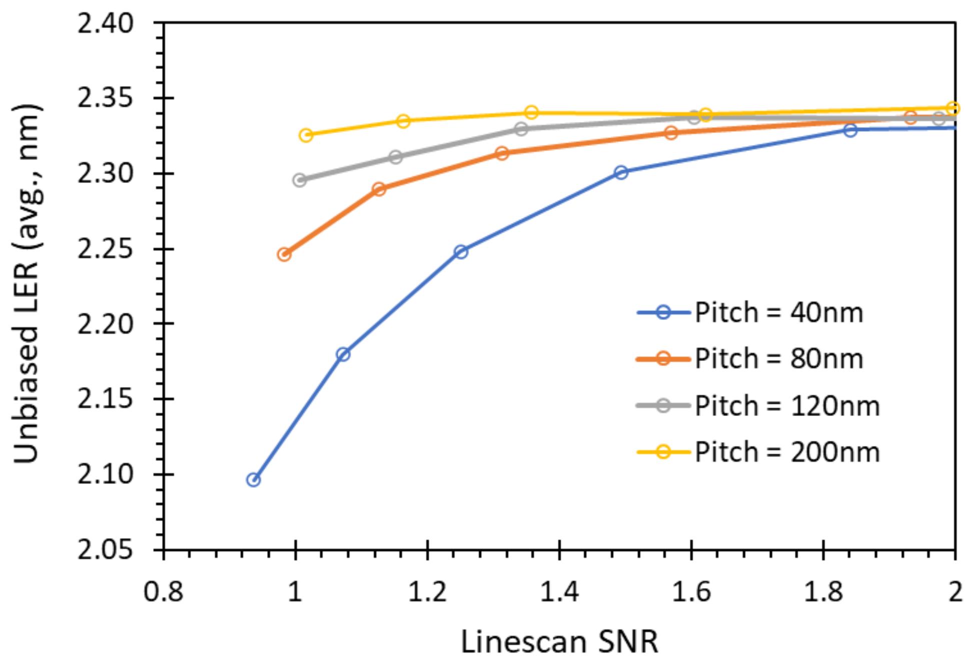


(b)

Figure 5. Measurements of synthetic SEM images show reduced SNR dependency for larger pitch patterns (nominally equal lines and spaces, 1.0 nm pixel sizes, and input LER of 2.4 nm): a) measured unbiased LER versus SNR, and b) a close-up view of this same data for SNR below 2.

IV. A MODEL FOR THE SNR DEPENDENCY OF UNBIASED LER

Consider the detection of an edge (or a linewidth from two edges) for a single row of pixels. The measured edge position w_{meas} is equal to the true edge position w_{true} plus an error e.

$$w_{meas} = w_{true} + e \tag{1}$$

Taking the variance of both sides of the equation,

$$VAR(w_{meas}) = VAR(w_{true}) + VAR(e) + 2Cov(w_{true}, e) \tag{2}$$

where $Cov(\mathrm{X}, Y)$ is the covariance of X and Y. Using the terminology of biased and unbiased LER, equation (2) becomes

$$\sigma_{biased}^2 = \sigma_{unbiased}^2 + \sigma_{noise}^2 + 2Cov(w_{true}, e) \tag{3}$$

where σ_{noise} is the edge detection noise. It is very common to assume that $Cov(w_{true}, e) = 0$, so that any error in edge detection is independent of the true edge position. This is the assumption made in essentially all attempts to unbiased a measured roughness,[1] and this assumption is made in MetroLER as it was used to measure the unbiased roughness presented above.

Is it possible that the covariance term in this equation is responsible for the observed SNR effect? Further insight can be gained by expressing the covariance in terms of a dimensionless correlation coefficient.

$$\sigma_{biased}^2 = \sigma_{unbiased}^2 + \sigma_{noise}^2 + 2\sigma_{unbiased}\sigma_{noise}Correlation(w_{true}, e) \tag{4}$$

Since $\sigma_{unbiased}$ is fixed in both the simulations and experiments presented in this paper, the additional covariance term will grow in proportion to the edge detection noise. In fact, a constant correlation coefficient on the order of -0.05 would provide something similar to the observed results. This result emphasizes the importance of keeping the edge detection uncertainty σ_{noise} as low as possible, for example by using an edge detection algorithm with as low a sensitivity to image noise as possible.[6]

The cause of correlation between the edge detection error and the true edge position can be seen by examining a basic edge detection error model. While there could be a number of mechanisms for edge detection uncertainty (such as errors in beam scan position or variations in charging), the grayscale noise in the image is an obvious culprit. Simplistically, the apparent edge position will shift for a given error in grayscale value at the edge (Δg) depending on the linescan slope at the edge (Figure 6).

$$e = \frac{\Delta g}{linescan\ slope} \tag{5}$$

We expect grayscale noise at the line edge to be independent of edge position, but if the linescan slope depends on edge position (w_{true}), then there would be a correlation between edge detection error and edge position through the change in linescan slope.

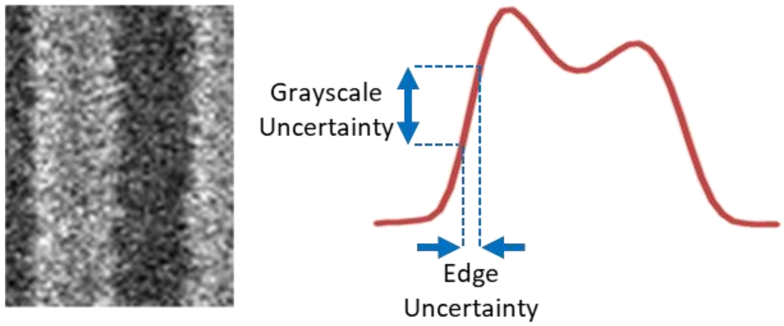


Figure 6. A simple model relates grayscale uncertainty in a SEM image to detected edge uncertainty depending on the linescan slope at the edge.

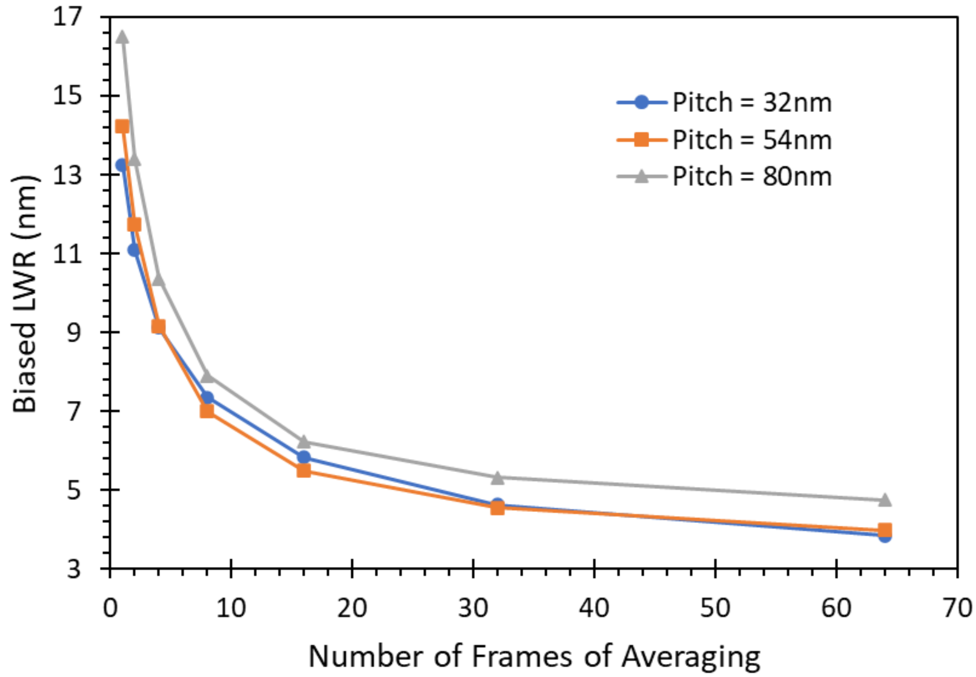
For dense patterns, the interaction of an electron beam with an edge depends on other close-by edges.[12] But as those edges move further apart, they interact less. For patterns with large lines and spaces, we would expect the linescan slope to be independent of small changes in the true edge position caused by the roughness of the feature. This is confirmed by the simulations shown in Figure 5.

V. EXPERIMENTAL CONFIRMATION OF THE PITCH DEPENDENCE OF THE SNR EFFECT

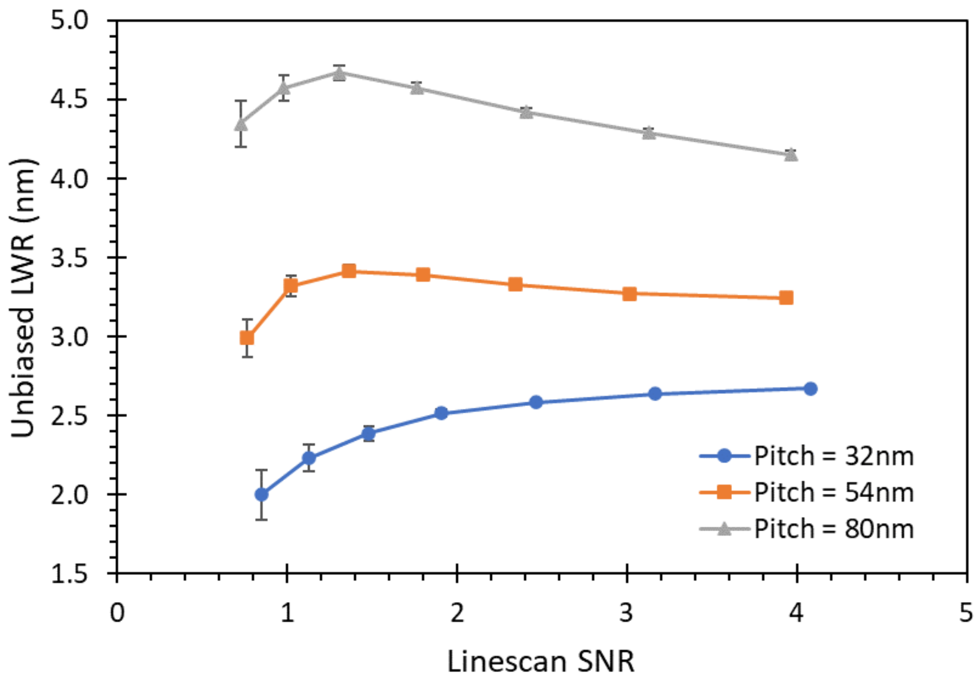
To experimentally verify the prediction that larger-pitch patterns will display reduced SNR influence on unbiased roughness, ADI images of nominally equal line/space patterns were collected as a function of the number of frames of averaging (from 1 to 64) for three different pitches: 32, 54, and 80 nm. The images were taken by a Hitachi CG6300 CD-SEM at 500 V, 50 images per condition, pixel size = 0.8 nm square, image size = 2048x2048, and resist thickness = 30 nm. The biased and unbiased roughness are shown in Figure 7.

The unbiased roughness in Figure 7b shows different behavior at larger pitches compared to the smallest pitch. For pitch = 32 nm, the behavior is as has been seen before, a fairly flat response at high SNR, but then the unbiased LWR falls off at SNR below about 2. For the larger pitches there are two distinct regions. For SNR above about 1.4, the unbiased roughness is decreasing as the SNR increases. This is likely due to resist shrinkage, with a proportional shrinkage in the roughness. At SNR below 1.4, the unbiased roughness falls off, but much less than was observed at the smaller pitch. For easier comparison, the data in Figure 7b was normalized so that the LWR for each pitch would be 1 at the highest SNR data point (see Figure 8).

From Figure 8 it is clear that the larger pitch patterns exhibit less variation in unbiased LWR as a function of linescan SNR, confirming the predictions of the synthetic SEM image modeling. Unlike the simulations, however, the ADI experimental data appears to show a resist shrinkage-induced smoothing that works oppositely of the apparent decrease in unbiased LWR as linescan SNR is reduced. For the smallest pitch, a likely smaller shrinkage is not noticeable in the presence of a larger SNR effect. For the larger pitches, both shrinkage and a much-reduced SNR effect are clearly observable.



(a)



(b)

Figure 7. Roughness measurements as a function of the number of frames of averaging (ADI measurements from Hitachi CG6300, pixel size = 0.8 nm square, image size = 2048x2048, 50 images per condition, equal lines/space patterns with pitch = 32, 54, and 80 nm). a) biased LWR as a function of the number of frames of averaging, and b) unbiased roughness as a function of the linescan signal-to-noise ratio.

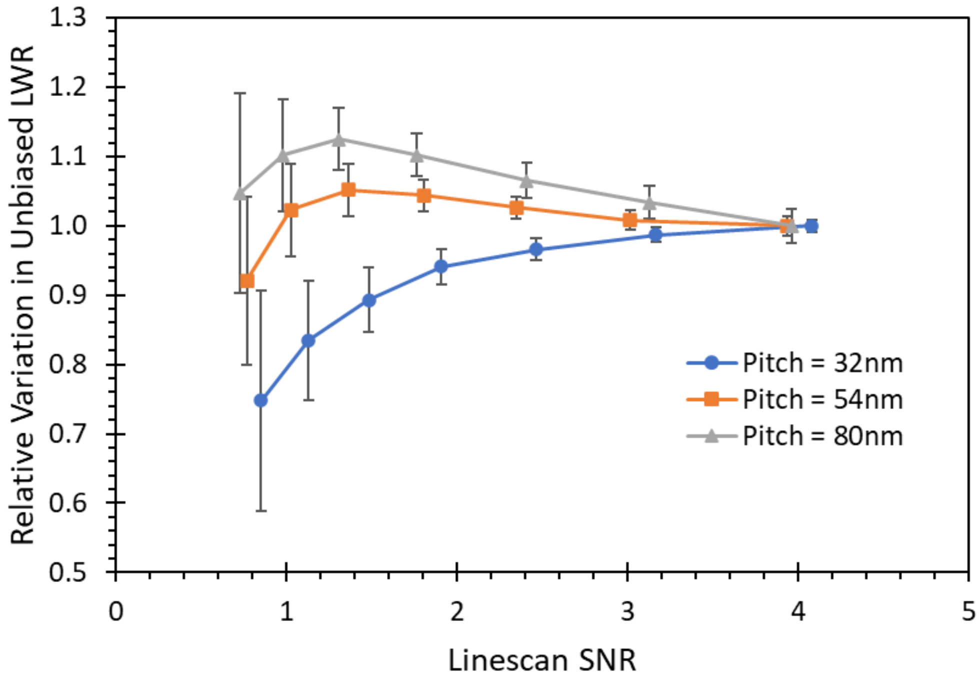


Figure 8. The data from Figure 7b, normalized to be 1 for each pitch at the highest linescan SNR.

VI. CONCLUSIONS

One of the standard tests for the efficacy of a CD-SEM roughness measurement unbiasing algorithm is to measure the same wafer using different numbers of frames of averaging, then compare the unbiased LER or LWR. Since lower frames of averaging results in noisier images, the biased LER/LWR varies considerably (often by more than a factor of 2). The goal of an unbiasing algorithm is to remove the contribution of SEM noise to the measurement and produce a measurement that reflects the true roughness on the wafer. Thus, we hope for the same unbiased LER/LWR result for all frames of averaging.

Various factors conspire to prevent perfectly consistent unbiased roughness as a function of the number of frames of averaging. Physically, the patterns on the wafer can change as a function of the number of frames due to both sample damage (such as resist shrinkage) and sample charging during measurement. But the algorithms that measure and statistically subtract the contribution of SEM edge detection noise from the biased roughness can also be imperfect. In previous work and in this paper, the average linescan signal-to-noise ratio was shown to be a sensitive indicator of the difficulty in determining unbiased roughness: using MetroLER, SNR above 2 produces reliable unbiased roughness, but below 2 the unbiased roughness is reduced as the SNR is reduced.

In this work, mathematic analysis, synthetic SEM image modeling, and experimental data all point to a correlation between edge detection noise and the true edge position (which varies due to roughness) as the cause of this SNR dependency in the accuracy of the standard unbiasing approach. For small pitch patterns, changes in edge position due to roughness result in a slight change in the average linescan slope, which then changes the edge detection noise. Thus, the assumption of a constant edge detection noise, used by all the unbiasing algorithms, becomes less accurate. Larger pitch patterns exhibit less change in linescan slope with edge position, and thus less SNR dependency.

This study has shown at least one possibility for reducing the SNR effect: using a smaller pixel size. Further work may enable the measurement of the correlation coefficient between edge detection error and the true edge position, resulting in a more accurate unbiasing algorithm. In the meantime, the guideline of trying to keep the linescan SNR above 2 for accurate unbiased LER/LWR measurement using Fractilia's software is an important one. For edge detection algorithms with greater sensitivity to image noise, the minimum SNR for accurate unbiasing is likely higher. The SNR sensitivity of other algorithms should be evaluated before use.

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