Comparing Edge Detection Algorithms: their impact on unbiased roughness measurement precision and accuracy

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Abstract

Background: Understanding line-edge and linewidth roughness in semiconductor patterning requires accurate, unbiased measurements where noise in the scanning electron microscope (SEM) image does not impact the measured roughness. This in turn requires edge detection algorithms with minimum sensitivity to SEM noise since unbiased roughness measurement does not allow the use of image filtering.
Aim: There is a need to characterize and evaluate the noise sensitivity of edge detection algorithms used in SEM metrology.
Approach: The noise floor of the roughness power spectral density will be used as a metric of noise sensitivity to compare three edge detection algorithms (derivative, threshold, and Fractilia Inverse Linescan Model (FILM)) using three sets of images (low-noise, mid-noise, and higher-noise cases).
Results: The derivative edge detection algorithm performed poorly even on low-noise images. The threshold algorithm worked well only on the low-noise images. For all levels of noise in the images, the FILM algorithm performed well, and better than the threshold and derivative methods.
Conclusions: An approach to unbiased roughness measurement that requires measurement of the noise floor without the use of image filtering requires an edge detection algorithm with inherently low noise sensitivity. The testing approach used here, comparing the noise floor level for different algorithms applied to the same images, is an effective way to evaluate the inherent noise sensitivity of edge detection algorithms.

Keywords: Power Spectral Density, PSD, line-edge roughness, linewidth roughness, LER, LWR, unbiased roughness, CD-SEM, noise floor

I. INTRODUCTION

Stochastics effects in lithography, such as line-edge roughness (LER), linewidth roughness (LWR), local critical dimension uniformity (LCDU), local edge placement error (LEPE), and stochastic defects, continue to grow in importance as feature sizes shrink in semiconductor manufacturing. Roughly speaking, stochastics effects grow as the inverse of minimum feature size to the 3/2 power.[1-3] The growing importance of LER and LWR increases the importance of proper measurement of these quantities. The most popular metrology tool for the measurement of LER and LWR is the critical dimension scanning electron microscope (CD-SEM). Top-down CD-SEM images are analyzed to detect feature edges, which are then characterized by a standard deviation of linewidth (for LWR) or edge position (for LER) variation along the length of the feature. Unfortunately, noise in the SEM image is easily confused for roughness along the edge of the feature, biasing measured roughness higher.[4]

Recently, an effective approach for measuring and subtracting the impact of SEM image noise from biased roughness measurements to produce unbiased roughness measurements has become available.[5-9] This technique requires that edges be detected without the use of image filtering, so that a clear noise floor is produced in the roughness power spectral density (PSD). The noise floor is then measured and used to statistically subtract the metrology noise contribution from the biased roughness to produce an unbiased roughness estimate. The requirement of no image filtering is critical, since the use of filtering removes the noise floor necessary for the statistical unbiasing. This in turn means that the edge detection algorithm used must robustly find the edges even for very noisy images. Since different edge detection algorithms have

different inherent sensitivity to image noise, a technique for evaluating the noise sensitivity of edge detection algorithms is needed.

In this paper, a method for evaluating the inherent noise sensitivity of different edge detection algorithms is proposed. The technique requires SEM image sets of varying noise levels (for example, by changing the number of frames of averaging). Edge detection algorithms are compared by generating PSDs based on the different algorithms operating on the given sets of images. The noise-floor level of these PSDs is a measure of the inherent noise sensitivity of the algorithm and can be used to choose the most appropriate algorithm for unbiased roughness measurement.

II. MEASURING UNBIASED ROUGHNESS – A REVIEW

The description of unbiased roughness measurement here follows that given in Ref. 3.

SEM images suffer from shot noise, where the number of electrons detected for a given pixel varies randomly, and further noise is added due to amplification and the electronic channel that turns the number of detected electrons into a grayscale pixel value. For an idealized Poisson distribution, the variance in the number of electrons detected for a given pixel of the image is equal to the expected number of electrons detected for that pixel, and the relative uncertainty in the detected signal goes as one over the square root of the number of detected electrons. Since the number of detected electrons is proportional to the number of electrons that impinge on the sample, pixel noise can be reduced by increasing the electron dose that the sample is subjected to during SEM measurement. For some types of samples, electron dose can be increased over a moderate range with few consequences. But for other types of samples (especially photoresist), high electron dose leads to sample damage (resist line slimming, for example). Thus, to prevent sample damage electron dose is kept as low as possible, where the lowest dose possible is limited by the noise in the resulting image. Figure 1 shows portions of three SEM images of nominally the same lithographic features taken at different electron doses. In most SEMs, the electron dose is conveniently changed by changing the number of frames of averaging (each frame being a single scan of the beam of electrons across the sample).

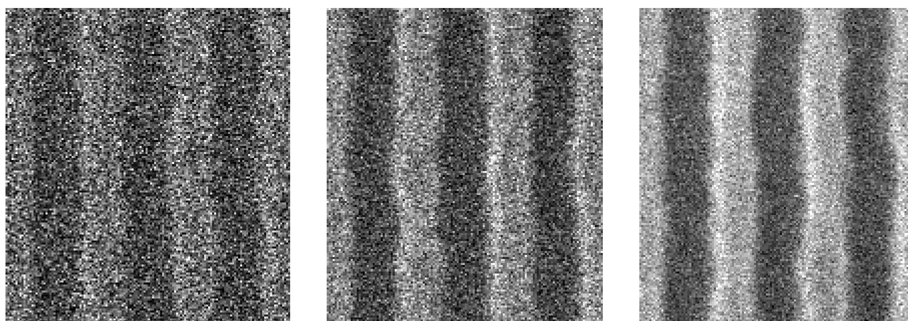


Figure 1. Portions of SEM images of nominally identical resist features with 2, 8, and 32 frames of integration (respectively, from left to right). Doubling the frames of integration doubles the electron dose per pixel. Since the dose is increased by a factor of 4 in each case, the noise goes down by a factor of 2. Figure from Ref. 3.

Random pixel grayscale variations produce edge detection variations, where the uncertainty in the grayscale level combines with the slope of the mean linescan shape at the feature edge to produce an uncertainty in detected edge position. Making the very reasonable assumption that the amount of edge detection noise in a SEM is independent of the amount of actual roughness of the feature, SEM edge detection

noise adds to the roughness of the patterns on the wafer to produce a measured roughness that is biased higher.[4]

$$\sigma_{biased}^2 = \sigma_{unbiased}^2 + \sigma_{noise}^2 \tag{1}$$

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. Since an unbiased estimate of the feature roughness is obviously what is desired, the measured roughness must be corrected by subtracting an estimate of the noise term.

Measuring the edge detection noise term can be accomplished using the power spectral density (PSD). The PSD is the variance of the edge (deviations measured perpendicular to the ideal edge) per unit frequency (Figure 2), and is calculated as the square of the coefficients of the Fourier transform of the edge or width deviation. The low-frequency region of the PSD curve describes edge deviations that occur over long length scales, whereas the high-frequency region describes edge deviations over short length scales. Commonly, PSDs are plotted on a log-log scale. The PSD of lithographically defined features generally has a shape similar to that shown in Figure 2. The low-frequency region of the PSD is flat (so-called "white noise" behavior), then above a certain frequency it falls off as a power of the frequency (a statistically fractal behavior). The difference in these two regions has to do with correlations along the length of the feature. Points along the edge that are far apart are uncorrelated with each other (statistically independent), and uncorrelated noise has a flat power spectral density. But at short length scales the edge deviations become correlated, reflecting a correlating mechanism in the generation of the roughness, such as acid reaction-diffusion for a chemically amplified resist.[10] The transition between uncorrelated and correlated behavior occurs at a distance called the correlation length.

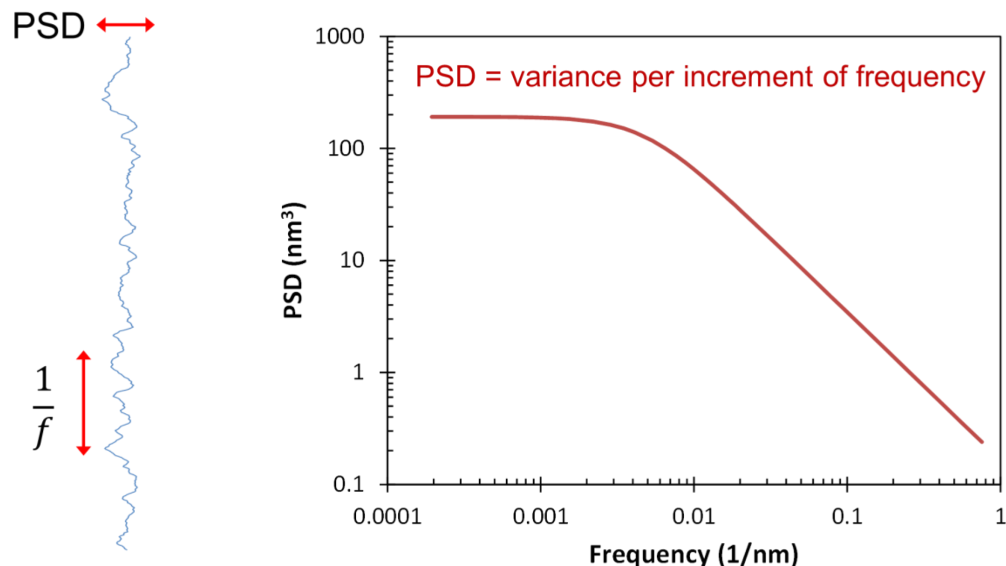


Figure 2. An example of a rough edge and its corresponding power spectral density (PSD). Figure from Ref. 3.

Noise measurement and subtraction can be achieved by contrasting the PSD behavior of the noise with the PSD behavior of the actual wafer features. We expect resist features (as well as after-etch features)

to have a PSD behavior as shown in Figure 2. Correlations reduce high-frequency roughness so that the roughness becomes very small over very small length scales. SEM image noise, on the other hand, can be reasonably assumed to be white noise, so that the noise PSD is flat.[8] Thus, at a high enough frequency the measured PSD will be dominated by image noise and not actual feature roughness (the so-called "noise floor").[1] Given the grid size along the length of the line (Δy), SEM noise affects the PSD according to[11]

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

Thus, measurement of the high-frequency PSD (in the absence of any image filtering, to be discussed below) provides a measurement of the SEM edge detection noise. Figure 3 illustrates this approach.

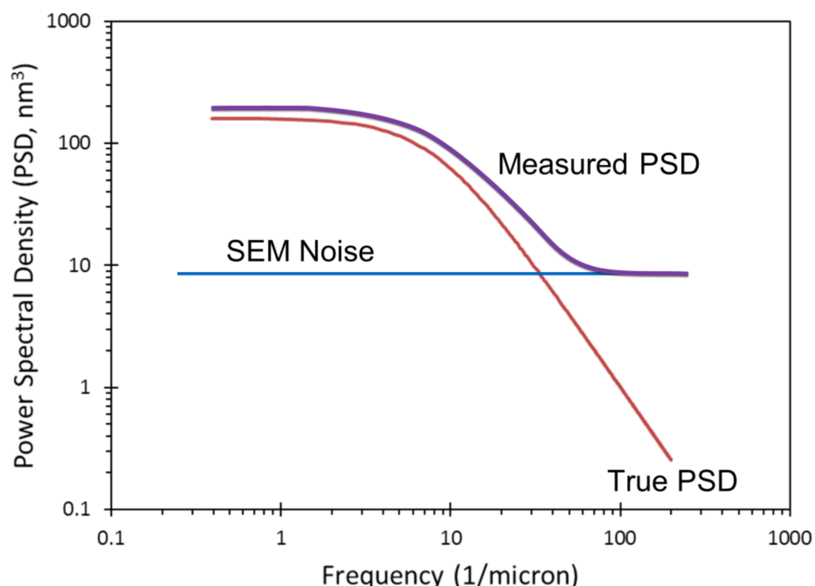


Figure 3. The principle of noise subtraction: using the power spectral density, measure the flat noise floor in the high-frequency portion of the measured PSD, then subtract this white noise from the measured PSD to get an estimate of the true PSD. Figure from Ref. 3.

In a prior study,[9] the capabilities of the above unbiased roughness measurement method were tested by measuring a given wafer using SEM images captured with varying number of frames (and thus varying amounts of SEM image noise). Ideally, an unbiased measurement of LWR would produce the same results regardless of the number of frames of averaging (though the error bars on the measured LWR would differ) and without the need to adjust the measurement or algorithm settings. Thus, comparing unbiased LWR measurements through numbers of frames of averaging provides a clear test of an unbiased roughness measurement approach. Figure 4(a) shows the biased LWR PSDs that were generated, and Figure 4(b) shows the unbiased PSDs after the SEM noise floor was measured and subtracted out. The collapsing of the disparate biased PSD curves in Figure 4(a) into a single unbiased PSD curve of Figure 4(b) indicates the success of the unbiasing approach. Figure 5 compares the biased and unbiased LWR as a function of the number of frames. Clearly the act of unbiasing the measured LWR produces a result that is very stable over a wide range of number of frames. The prior study showed similar results for after-litho SEM images versus number of frames as well.[9]

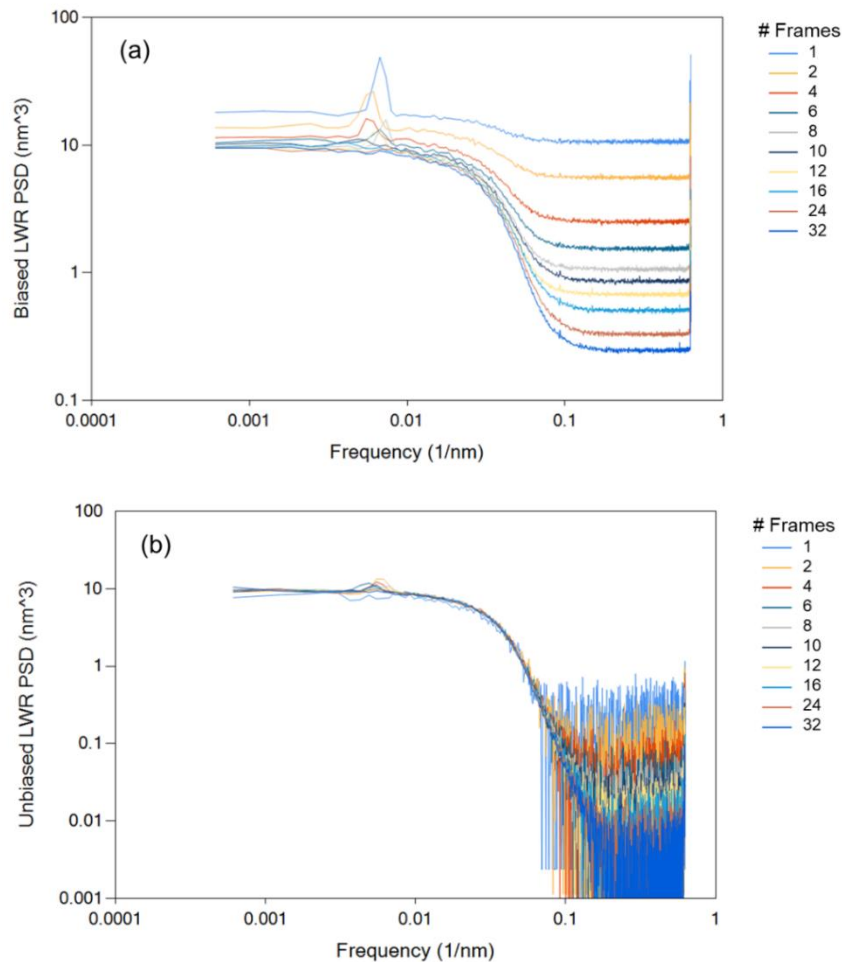
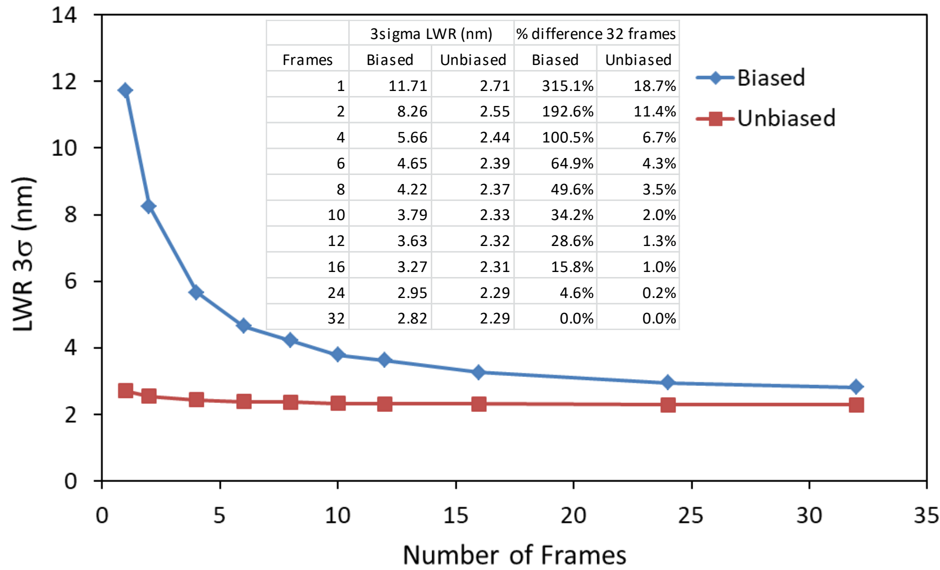


Figure 4. Power spectral densities (PSDs) of 32 nm pitch etched lines and spaces where only the number of frames of integration was varied. (a) biased LWR PSDs based on the as-detected features, and (b) unbiased LWR PSDs after measurement and subtraction of the noise floor. SEM conditions: 800 eV, 50 images per condition, about 50 features per image, pixel size = 0.8 nm square, image size = 2048×2048 pixels. Figure from Ref. 9.

The key to using the above approach of noise subtraction for obtaining an unbiased PSD (and thus unbiased estimates of the LER and LWR) is to robustly detect edges without the use of image filtering. Filtering (smoothing of the grayscale image noise) is commonly used to improve edge detection robustness for standard critical dimension metrology. For high levels of image noise, a simple edge detection algorithm such as threshold edge detection may detect mostly image noise rather than the actual edge position, thus necessitating the use of image filtering. But image filtering removes the very noise floor required to produce an unbiased roughness estimate (Figure 6). For this reason, unbiased roughness measurement requires robust detection of feature edges without the use of image filtering. In other words, unbiased roughness measurement requires an edge detection algorithm with low inherent sensitivity to image noise.



	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 from Ref. 9.

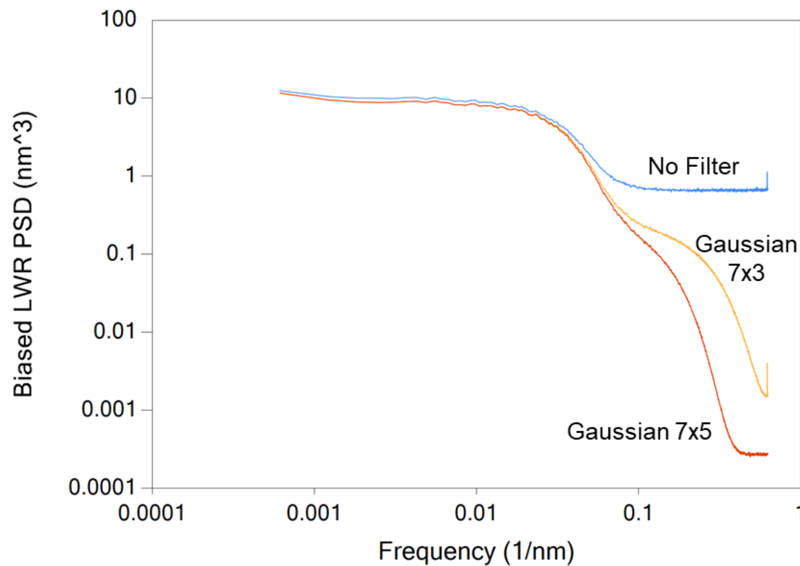


Figure 6. Power spectral densities from many rough features with images preprocessed using a 7x3 or 7x5 Gaussian filter, or not filtered at all. Similar results are obtained when using a box (mean) filter. Edge detection used a simple threshold algorithm with images described in the text as the "low-noise" case.

III. COMPARING THE NOSIE SENSITIVITY OF EDGE DETECTION ALGORITHMS

Since image filtering cannot be used for unbiased roughness measurements, we require an edge detection algorithm with low inherent sensitivity to image noise. Here, the noise sensitivity of three different edge detection algorithms will be compared by measuring the noise floor for different groups of SEM images. A

subset of the SEM images used in Ref. 9 will be used here. Two wafers were used, one after lithography and one after pattern etch into an oxide film stack, each with 32 nm pitch lines and spaces produced at imec with EUV single patterning. The three groups of SEM images are detailed in Table I. All images were 2048x2048 pixels with a square pixel size of 0.8 nm and were obtained on a Hitachi CG-5000 CD-SEM at imec. Approximately 50 lines and spaces were measured for each image, and 50 images were used for each group.

Table I. Wafer and SEM measurement conditions for the three groups of images used in this study.

SEM Group Name	Wafer	SEM Conditions
Low-Noise	After-Etch	800 V, 32 frames
Mid-Noise	After-Litho	500V, 16 frames
Higher-Noise	After-Litho	500 V, 8 frames

Three edge detection algorithms will be compared. The first is a standard threshold algorithm with threshold set at 0.5 (the grayscale threshold was set to 50% between the minimum and maximum grayscale level of the average linescan). The second is a derivative edge detector using a Sobel 5x1 filter. The final edge detection algorithm is the second generation Fractilia Inverse Linescan Model (FILM).[5,5] All algorithms were used as implemented in MetroLER v2.1 (from Fractilia). Each algorithm was applied to the three groups of images and their results compared.

Figure 7 shows the biased LWR PSDs for each image set and each edge detection algorithm, with the noise floor indicated. It is clear from all sets of images that the FILM edge detection algorithm has the lowest noise floor, and thus the least sensitivity to image noise. The inverse modeling approach to edge detection uses the physics of linescan generation to extract signal and reject noise, making it fundamentally less sensitive to noise than the other compared algorithms. As expected, the derivative algorithm is the most noise-sensitive, with threshold intermediate. From Figure 7(a), for the low-noise images all edge detection algorithms provide a clear noise floor that is noticeably lower than the “signal”, the low-frequency plateau of the PSD. For the mid-noise and higher-noise cases, the distinction between signal and noise is only clear for the FILM edge detection.

In Figure 8, the measured edge detection noise is subtracted from the biased PSD and the unbiased LWR is calculated and compared for each edge detection algorithm. For the low-noise images (Figure 8(a)), FILM and threshold unbiased LWR differ by only 1%, though the error bars for the threshold results are larger. The Sobel/derivative case is about 10% higher than the other two – a significant difference. Additionally, for the low-noise images the unbiased PSDs match for threshold and FILM, but the Sobel case is significantly different. For these low-noise images, FILM performs the best, but threshold edge detection is acceptable as well.

In Figure 8(b), for the mid-noise after-litho images, the threshold algorithm is clearly beginning to fail. While the 3σ unbiased LWR for threshold is down only 5% compared to FILM, its error bars are considerably larger. More troubling, the unbiased PSD using threshold edge detection does not exhibit the expected shape (flat at low frequencies), while the FILM result does. For the higher-noise images (Figure 8(c)), only FILM provides a reasonable result (the threshold algorithm produces a 3σ unbiased LWR that is 2X below the FILM value).

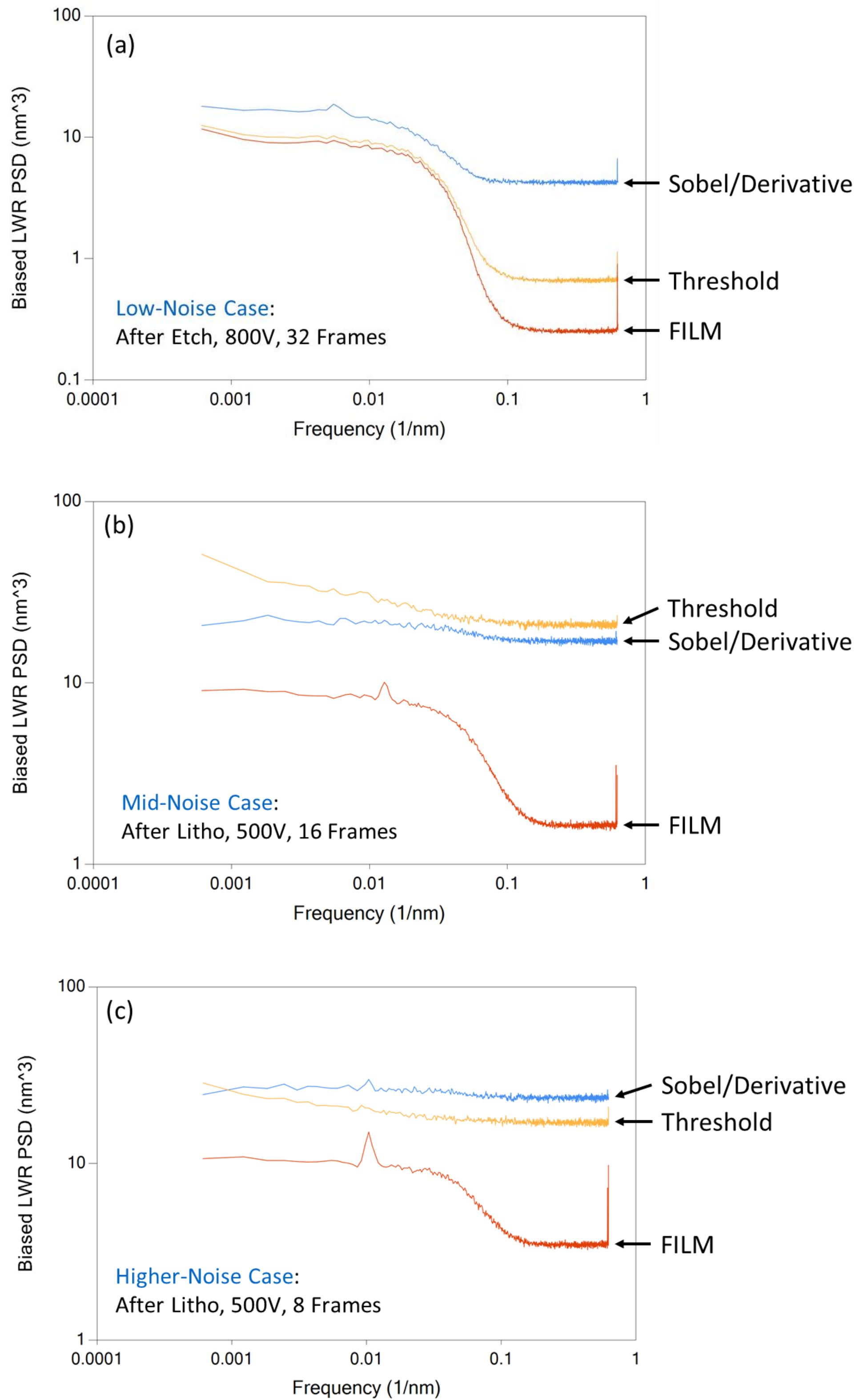


Figure 7. Biased LWR power spectral densities for the three different edge detection algorithms tested (Sobel/derivative, threshold, and FILM) for the three different groups of SEM images: (a) low-noise, (b) mid-noise, and (c) higher-noise images.

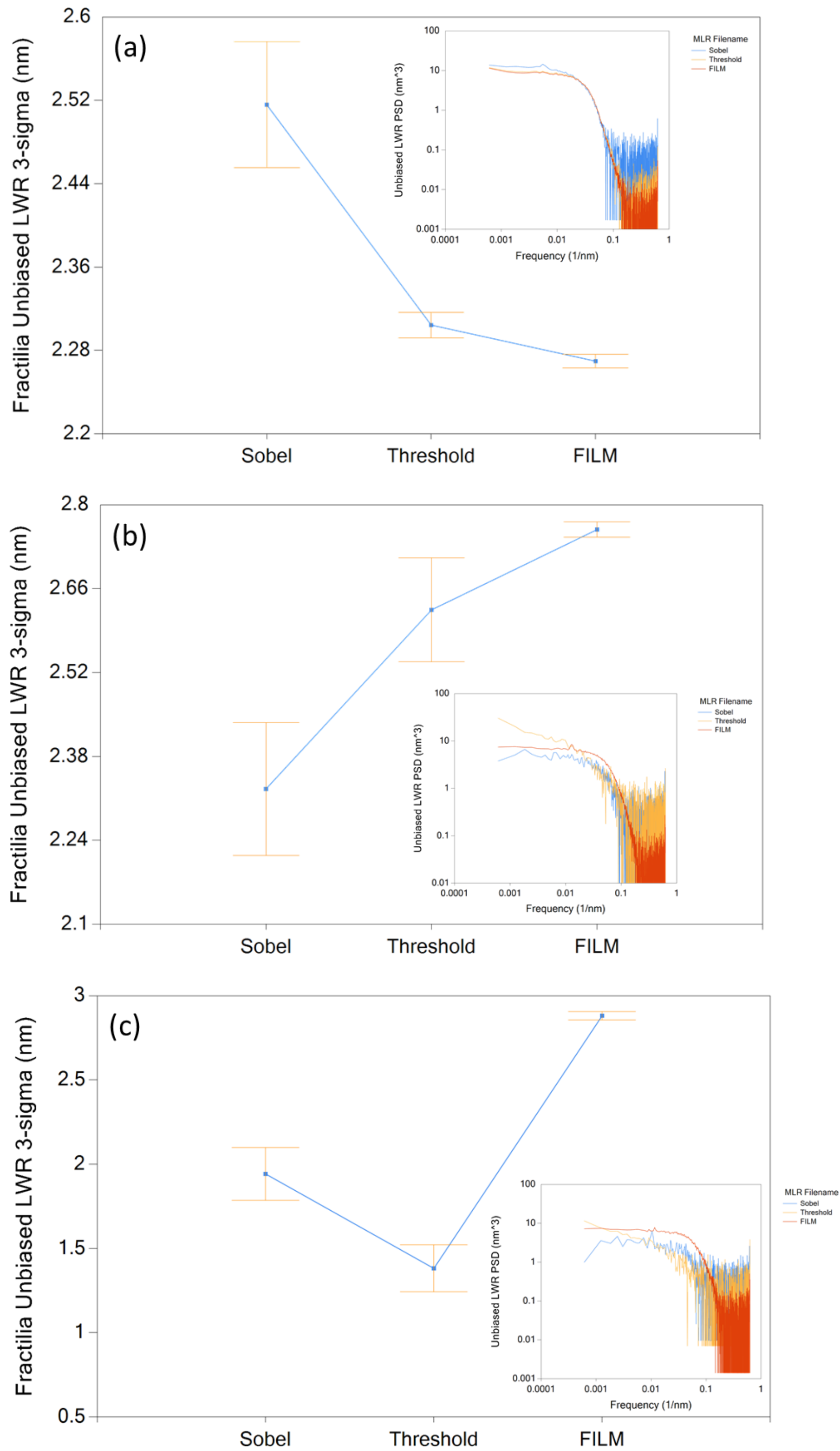


Figure 8. Unbiased LWR power spectral densities and 3σ LWR for the three different edge detection algorithms tested (Sobel/derivative, threshold, and FILM) for the three different groups of SEM images: (a) low-noise, (b) mid-noise, and (c) higher-noise images.

Another way to compare these edge detection algorithms is to calculate signal-to-noise ratios. The signal here can be defined as the zero-frequency PSD, called PSD(0), of the unbiased LWR. This value can be obtained by fitting the unbiased PSD to a model.[3] The ratio of unbiased PSD(0) to the noise floor obtained from the biased PSD can be defined as the signal-to-noise ratio (SNR) for that edge detection algorithm as applied to that set of images. Table II provides the results of SNR calculations for all cases. Comparing these values to the graphs and discussion above, it appears that an SNR of about 1 or greater is needed to obtain reasonable results in determining unbiased roughness. Such an SNR cut-off, however, will depend greatly on the number of feature PSDs being averaged together (that is, on the uncertainty in determining the noise floor and PSD(0)).

Table II. Signal-to-noise ratios (SNR) for the different edge detection methods applied to the different SEM image groups.

	Sobel/Derivative	Threshold	FILM
Higher-noise	0.14	0.30	1.8
Mid-noise	0.28	0.63	4.0
Low-noise	2.7	12	31

IV. EDGE-PRESERVING FILTERS

As seen in Figure 6, applying an averaging filter in the y-direction destroys the noise floor and makes unbiased roughness calculations impossible. The filter used was a simple averaging filter, where the grayscale value of any given pixel is set to be the average of it and its neighbors over a range defined by the filter size (and possibly weighted before averaging, for example using Gaussian weights). But there are other filter types beside simple averaging filters, and in particular edge-preserving filters, that could also be applied. Here, three edge-preserving filters will be tested to determine if they are appropriate for unbiased roughness measurement.

The simplest edge-preserving filter is the median filter, where the grayscale value of a pixel is replaced by the median grayscale value of all pixels within the filter range. Another important class of edge-preserving filters is the bilateral filter,[12] where a smoothing filter is applied (for example, a Gaussian filter), but the amount of smoothing is reduced when the difference in grayscale values of neighboring pixels is high (such as when close to an edge). Here, a two-Gaussian bilateral filter (a bilateral filter with Gaussian kernels) will be used. Finally, the Mean of Least Variance (MLV) filter will be used as well.[13]

There are two questions that should be answered when considering the use of edge-preserving filters: Does the filter enable precise low-biased direct measurement of roughness (with results that do not depend on arbitrary filter settings), and if not, does it allow for measurement of the noise floor for calculation of unbiased roughness? For the case of simple averaging filters, these two questions have been definitely answered with “no”.[5,14] Here, we investigate the answers to these questions using three edge-preserving filters. Table III shows the resulting biased LWR values for the mid-noise data set after applying the bilateral filter. Similar results were obtained using the median and MLV filters. Clearly, changing arbitrary filter settings results in large variations in the biased LWR measurement, making edge-preserving filters a non-solution to the problem of biased roughness measurement.

Table III. Biased LWR (in nanometers) as a function of bilateral filter size (the x-direction is perpendicular to the feature edge).

	y-width = 1	y-width = 3	y-width = 5	y-width = 7
x-width = 1	15.57	15.04	13.91	13.16
x-width = 3	15.00	13.39	11.97	11.25
x-width = 5	13.83	11.86	10.54	9.99
x-width = 7	12.88	10.90	9.73	9.33
x-width = 9	12.14	10.24	9.21	8.90
x-width = 11	11.56	9.75	8.83	8.59

Examining the biased LWR PSDs after applying the edge-preserving filters likewise shows that the noise floor is destroyed using the filters, just as in the case of simple averaging filters (see Figure 9 for an example). Additionally, the unbiased LWR obtained after using the bilateral filter varied significantly with filter size, as expected because of the varying noise floor. The results for median and MLV filters were similar, indicating that the so-called edge-preserving filters still modify the edges too much for their use in roughness measurement.

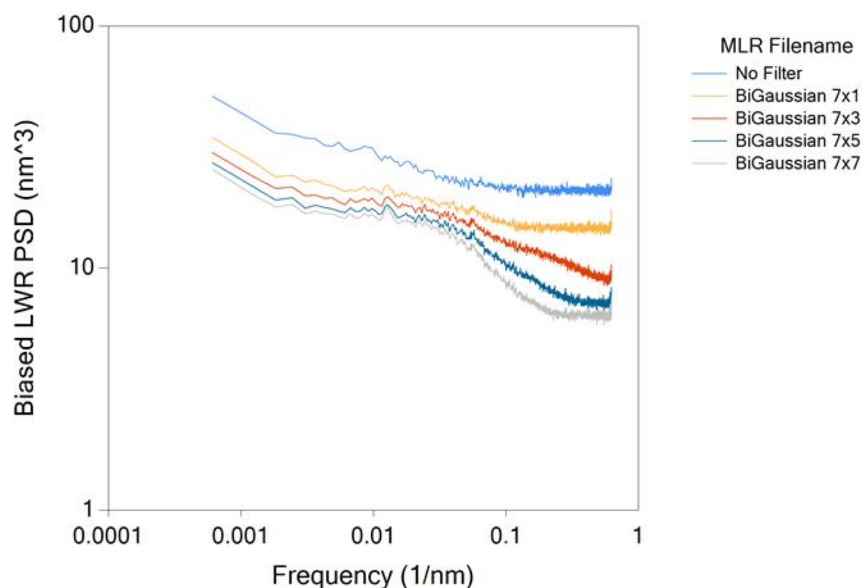


Figure 9. Power spectral densities from many rough features with the mid-noise images preprocessed using a bilateral filter with Gaussian kernels, or not filtered at all. Similar results are obtained when using median and MLV filters. Edge detection used the threshold algorithm.

V. CONCLUSIONS

Unbiased roughness measurement requires robust edge detection without the use of image filters. This in turn requires that the edge detection algorithm used has low inherent noise sensitivity. Here, a method for evaluating the noise sensitivity of an edge detection algorithm is proposed based on a measurement of the PSD noise floor. An algorithm with a lower PSD noise floor for a given set of images has less noise sensitivity. A signal-to-noise ratio can also be defined and used to the same effect. Using this noise sensitivity evaluation technique, three edge detection algorithms were compared: Sobel/derivative, threshold, and FILM (Fractilia Inverse Linescan Model). For three sets of images, varying from low to high noise, the FILM edge detection provided the least sensitivity to image noise.

VI. ACKNOWLEGEMENTS

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