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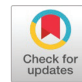

Determining the ultimate resolution of scanning electron microscope-based unbiased roughness measurements. I. Simulating noise

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Measuring line-edge roughness in a top-down scanning electron microscope (SEM) is complicated by noise in the SEM image, which biases the measured roughness. When either the roughness is small or the noise is large, it can become very difficult to separate noise from roughness to produce an unbiased estimate of the feature roughness. Synthetic SEM images with known roughness and noise properties can be used to explore the ultimate limits of SEM-based roughness metrology, but only if the noise in the synthetic images mimics the noise behavior of real images. By carefully analyzing the properties of experimental SEM images as a function of the number of frames of averaging (which directly modulates SEM noise), a noise model is developed. This model uses a Gamma distribution for the grayscale noise and then scales the image so that no more than 0.3% of the pixels are pegged at the maximum grayscale value of 255. The resulting synthetic SEM images mimic experimental SEM images in both signal and noise and will serve as a valuable tool for studying roughness metrology. *Published by the AVS.* https://doi.org/10.1116/1.5122758

I. INTRODUCTION

The most common method for measuring line-edge roughness (LER) and linewidth roughness for lithographically patterned features in semiconductor manufacturing (and other nanofabrication applications) uses images from a top-down scanning electron microscope (SEM). The basic steps in the measurement process are as follows: (1) create an image of the sample; (2) detect the rough edges of each feature in the image; and (3) determine roughness as three times the standard deviation of the edge (or width between two edges) compared to an estimate of the ideal edge (or width). In this simple approach, the resulting roughness will be biased by noise in the SEM image. In other words, noise in the SEM image produces noise in the detected edge positions that adds in quadrature with the actual edge roughness to produce a measure of roughness that is biased higher than the actual roughness.[1] For unbiased roughness estimation, two subsequent steps are added to the measurement process: (4) estimation of the noise in the detected edges due to SEM metrology and (5) subtraction of the estimated metrology noise from the biased roughness measurement to produce an unbiased roughness measurement.

In previous studies, a new technique for producing unbiased estimates of roughness parameters was investigated.[2–4] It is based on the use of an analytical model for SEM scattering behavior that predicts linescans for a given feature geometry. Run in reverse, an inverse linescan model can be used for edge detection in such a way that SEM noise can be adequately measured and statistically subtracted from the roughness measurement, thus providing unbiased estimates of the roughness parameters. These previous studies investigated the impact of SEM pixel size/magnification, the number of measurement frames averaged (i.e., electron dose), SEM voltage, and multiple CD-SEM tools when measuring the same wafers. While the true unbiased roughness was identical (since all measurements involved the same wafers), the biased roughness varied by more than a factor of 3 over the range of measurement conditions studied. These studies showed that in most cases the unbiased roughness measured over a wide range of SEM operating conditions varied by only a few percent, validating the effectiveness of the unbiased roughness measurement approach.[4]

In light of this demonstrated success in making unbiased roughness measurements, there is still a question as to the ultimate measurement resolution for unbiased roughness. In particular, it is unclear what the maximum ratio of noise to signal can be tolerated while still giving acceptable answers. In other words, how small can the true roughness be while still being accurately extracted from a noisy SEM image? Or, for a given amount of true roughness of the sample, how much SEM noise can be tolerated while still producing an acceptable estimate of the unbiased roughness? To answer these questions, simulations can be used to probe the efficacy of unbiased roughness measurement. By generating synthetic SEM images of lines and spaces with randomly rough features of predetermined statistical properties,[5] different amounts of noise can be added to those images. Analyzing these noisy SEM images as if they were experimentally generated, the measured statistical properties of the features can be compared to the true values (which served as inputs to the generated synthetic SEM images) as a function of the amount of noise.[6] In this way, we can probe the robustness of current methods of measuring roughness in the presence of very high levels of noise and very low levels of roughness.

The usefulness of this approach depends on how well the synthetic SEM images mimic the behavior of actual SEM

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images as might be measured from actual wafers. The generation of a synthetic SEM image involves three steps: (1) generation of "actual" feature edges with predetermined statistical roughness; (2) conversion of these edges to a noise-free SEM image; and (3) the addition of noise to the SEM image. Step one can be easily realized and has been extensively characterized.[5] Step two is more complex, and here the previously described Analytical Linescan Model will be used for the cases of resist on an organic underlayer and silicon features etched into silicon.[7,8] Step three, however, has not been adequately addressed in past work and is the subject of this paper.

Beginning with an experimental characterization of noise in SEM images, a simplified model for SEM image noise will be proposed. This model includes the possibility of adding noise to a synthetic grayscale SEM image so that the grayscale values exceed the allowed range of 0–255 (for an 8-bit image). Thus, a noise model must include a scaling algorithm that mimics the actual scaling used by commercial SEMs when translating detector signals into grayscale images.

II. IMPACT OF EDGE DETECTION NOISE ON ROUGHNESS MEASUREMENT

The biggest impediment to accurate roughness measurement is noise in the CD-SEM image. SEM images suffer from shot noise, where the number of electrons striking a detector for a given pixel varies randomly, followed by channel noise during the amplification of the detected signal to its final state.[9] For an idealized SEM imaging process, the number of detected secondary electrons is typically described as following a Poisson distribution, where 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. For a large mean number of detected electrons per pixel, the Poisson distribution is approximately Gaussian, but for a small mean number of detection events, the distribution will be skewed to the right. The real process of generating, detecting, and amplifying secondary electron signals is more likely a compound Poisson process and has a final signal distribution empirically observed to be closer to lognormal.[10] Here, actual SEM images taken at different

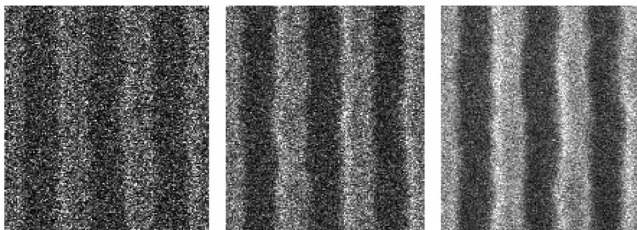


FIG. 1. Portions of SEM images of nominally identical 32-nm pitch resist features with 2, 8, and 32 frames of integration (respectively, from left to right). Doubling the frames of integration doubles the electron dose per pixel. Since the dose is increased by a factor of 4 in each case, the noise goes down by about a factor of 2. Reprinted from Chris A. Mack, J. Micro/Nanolithogr. MEMS MOEMS **17**, 041006 (2018). Copyright 2018, Society of Photo Optical Instrumentation Engineers.

electron doses will be used to explore the distribution of SEM image noise empirically. Figure 1 shows portions of three experimental SEM images of nominally the same lithographic features taken at different electron doses.[11]

Consistent with observed and expected behavior, we assume the SEM edge detection noise to be independent of the true feature roughness. SEM edge detection noise can be thought of as the interaction of grayscale pixel noise (statistical variations in the detected secondary electron signal for a given pixel) with the true (noiseless) linescan response of the edge to produce an uncertainty in the detected edge position. Since the grayscale pixel noise is a statistical phenomenon related to the mean (true) grayscale value, its fluctuations will be independent of the feature roughness. Under this assumption, SEM edge detection noise adds in quadrature to the actual roughness of the patterns on the wafer to produce a measured roughness that is biased higher,[12]

$$\sigma^2_{biased} = \sigma^2_{unbiased} + \sigma^2_{noise}, \tag{1}$$

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 the detected edge position (or linewidth) due to noise in the SEM imaging and edge detection. To obtain an unbiased estimate of the feature roughness, the measured roughness must be corrected by subtracting an estimate of the noise term.

The most common method for noise measurement uses the roughness power spectral density (PSD). The PSD is the variance of the edge per unit frequency and is calculated as the square of the coefficients of the Fourier transform of the edge 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 impact of SEM edge detection noise on the PSD can be modeled under a reasonable assumption that can be experimentally verified: edge detection noise is statistically independent of edge position. Statistical independence in the x-direction (perpendicular to the line edge) means that edge detection noise will add in quadrature to the actual roughness, as described in Eq. (1). Statistical independence in the y-direction (parallel to the line edge) means that edge detection noise will be white noise, with no correlations. Given the grid size along the length of the line (Δy), SEM edge detection white noise biases the PSD according to[13]

$$PSD_{biased}(f) = PSD_{unbiased}(f) + \sigma^2_{noise}\,\Delta y. \tag{2}$$

We expect lithographically patterned features to have an unbiased PSD behavior that is correlated at short length scales (high frequency) so that the roughness becomes very small at high frequencies. SEM image noise, on the other hand, is white noise so that the noise PSD is flat over all frequencies. Thus, at a high enough frequency, the measured

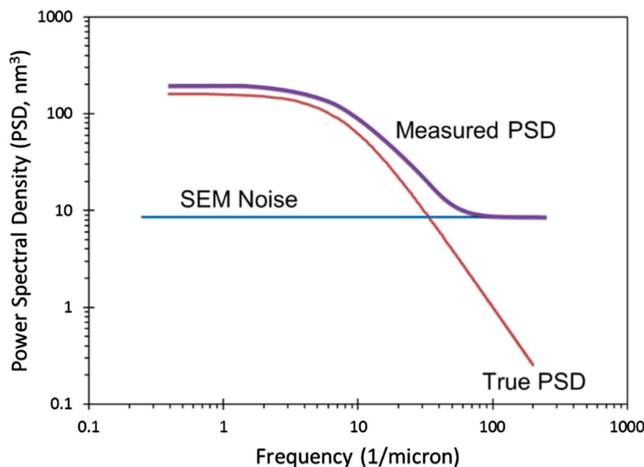


FIG. 2. Principle of noise subtraction: using the power spectral density, measure the flat noise floor in the high-frequency portion of the measured PSD, then subtract the white noise to get the true PSD (Ref. 11).

PSD will be dominated by image noise and not actual feature roughness (the so-called "noise floor").[14] Thus, measurement of the high-frequency PSD (in the absence of any image filtering) provides a measurement of the SEM image noise. Figure 2 illustrates this approach.

From the discussion above, the measurement of unbiased roughness involves first the measurement of the biased roughness from detected edges that include noise. Then, using the biased PSD the noise floor is detected so that an estimate of σ_{noise} is obtained. Finally, the noise estimate is used to create an unbiased estimate of the roughness according to Eq. (1). Uncertainty in the final unbiased roughness comes from uncertainty in the measurement of the biased roughness and uncertainty in the measurement of the edge detection noise. Note that any filtering of the image prior to edge detection will change the measured PSD (especially in the high-frequency region), making noise measurement and subtraction unreliable. In this study, the Fractilia Inverse Linescan Model will be used for all edge detection.[15]

III. MODELING SEM EDGE DETECTION NOISE

There are two potential types of SEM edge detection noise: errors in the (x,y) position of a pixel (x is perpendicular to the nominal feature edge) due to stage or beam drift and errors in the grayscale value of a pixel (called here "beam position noise" and "grayscale noise," respectively). These two sources of SEM noise will produce different impacts on measurement uncertainty based on their different probability distributions. From the perspective of creating synthetic SEM images, these two sources of noise are inserted into the SEM generation process at different points. The steps for generating a synthetic SEM image will be: (1) generation of "true" feature edges with predetermined statistical roughness; (2) addition of beam position noise as x-position noise to the edges (y-position noise will be assumed to have a negligible impact since its magnitude will be far less than the correlation length of the roughness); (3) conversion of these edges to a noiseless synthetic SEM image using the Analytical Linescan Model (for example); and (4) the addition of grayscale noise to each pixel in the SEM image.

Ideal (true) feature edges with random roughness that follows a given power spectral density can be generated using techniques previously described.[5] Beam position noise can be added to these rough edges by adding a simple Gaussian-distributed random deviation (mean zero, standard deviation of σ_{bp}) to each edge position at its sampled location in y. Two random edges (assumed to be uncorrelated with each other in this case) combine to form a line of a given mean width and combined with other features at a given mean pitch. Using a specified pixel size, the features are converted to SEM linescan data using the Analytical Linescan Model, assuming PMMA properties for both the feature and the substrate (equivalent to simulating resist on an organic underlayer) or etched silicon features.[7,8] The linescans were then converted to 8-bit grayscale values (integers in the range of 0–255), scaling the linescans to run between about 60 and 170 grayscale. This range corresponds to typical experimentally observed linescans at high numbers of frames. Note that the Analytical Linescan Model used here does not account for charging effects.

The next step, adding grayscale noise to the otherwise noiseless synthetic SEM, requires careful consideration. There are two questions that must be answered: what probability distribution best applies to added grayscale noise? And what happens when added noise creates a grayscale value greater than 255? Both of these questions are best answered by observing the behavior of experimental SEM images. Two different wafer features were examined: an isolated edge of resist on an amorphous carbon hardmask and linespace patterns of pitch = 32 nm. SEM images were taken on a Hitachi CG5000 at 500 V, 2048 × 2048 pixels, with a square pixel size of 0.8 nm. As is common in SEM metrology, the final image is the average of a specified number of single-frame images. A single-frame image comes from one complete raster scan of the sample by the electron beam. To reduce noise, multiple frames are captured by repeated scanning. Here, the number of frames of averaging was varied between 1 and 32 so that the total electron dose per pixel varied by a factor of 32.

Figure 3 shows example experimental SEM images and linescans of the isolated edge feature for the cases of 2 and 32 frames of averaging. The Single Linescan plot shows the grayscale values along one row of pixels across the image. The Average Linescan plot shows the grayscale values with each column of pixels in the y-direction averaged together. Figure 4 shows histograms of the grayscale distribution in each of the left and right side of the edge as a function of the number of frames of averaging. While these distributions are skewed right, they are not as heavily skewed as a lognormal. They are, however, well described by a Gamma distribution. (The skewness of the Gamma distribution is twice the ratio of the standard deviation to the mean. The skewness of the lognormal distribution is at least 1.5 times greater than that of the Gamma distribution for small skewness and twice that

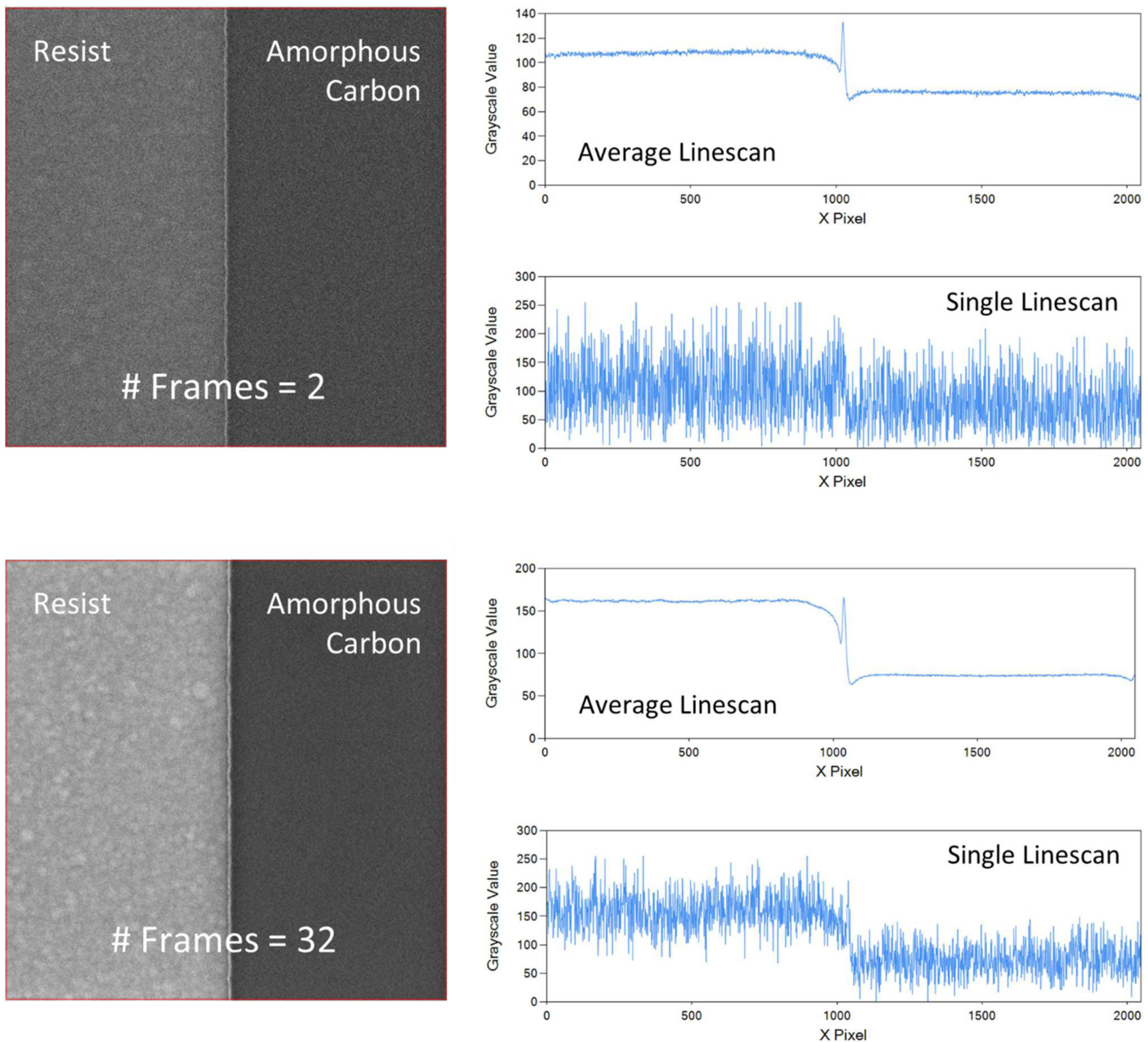


Fig. 3. Experimental SEM images of an isolated edge at 2 and 32 frames of averaging. Also shown are the average linescan (the average of all pixels in the y-direction) and a single linescan (an example of a single x-cut through the SEM image).

of the Gamma distribution for the case where the standard deviation equals the mean.) As seen in Fig. 5, the average grayscale value of the right side stays about the same as a function of the number of frames, but the average value of the right side increases with the number of frames, though it seems to level off. The standard deviations of the right and left side grayscale distributions decrease at about the same rate with increasing frames.

The behavior seen in Figs. 3–5 can be explained by the scaling step of generating an SEM image from a detector signal. The detected SEM image signal, including all noise, must be scaled and clipped to fit into a range of 0–255 gray levels. If the mean (or median or mode) of the image pixel values is scaled to be at, for example, a gray level of 128, the spread of grayscale values due to noise may extend far beyond that mean value. If any scaled pixel value extends beyond 255, it must be clipped to a value of 255. For a low-noise image (such as a 32 frame image), it will be rare for a pixel to reach 255, but for a high-noise image (say, two frames of averaging), many pixels could be clipped at 255.

Looking at the left side histograms of Fig. 4, an interesting observation can be made. In all cases, about 0.3% of the pixels of the whole image have a grayscale value of 255. This indicates that a scaling strategy like the following is probably being used: (1) scale the signal to have a mean (or median) value of 128 (or a similar value), (2) check to see if more than 0.3% of the pixels have values that equal or exceed 255; (3) if so, scale down the signal further until at most 0.3% of the pixels are at 255 or greater; and (4) clip any pixel values greater than 255 to be 255. The consequences of this scaling strategy are twofold. First, an acceptably small number of pixels will have clipped grayscale values regardless of the

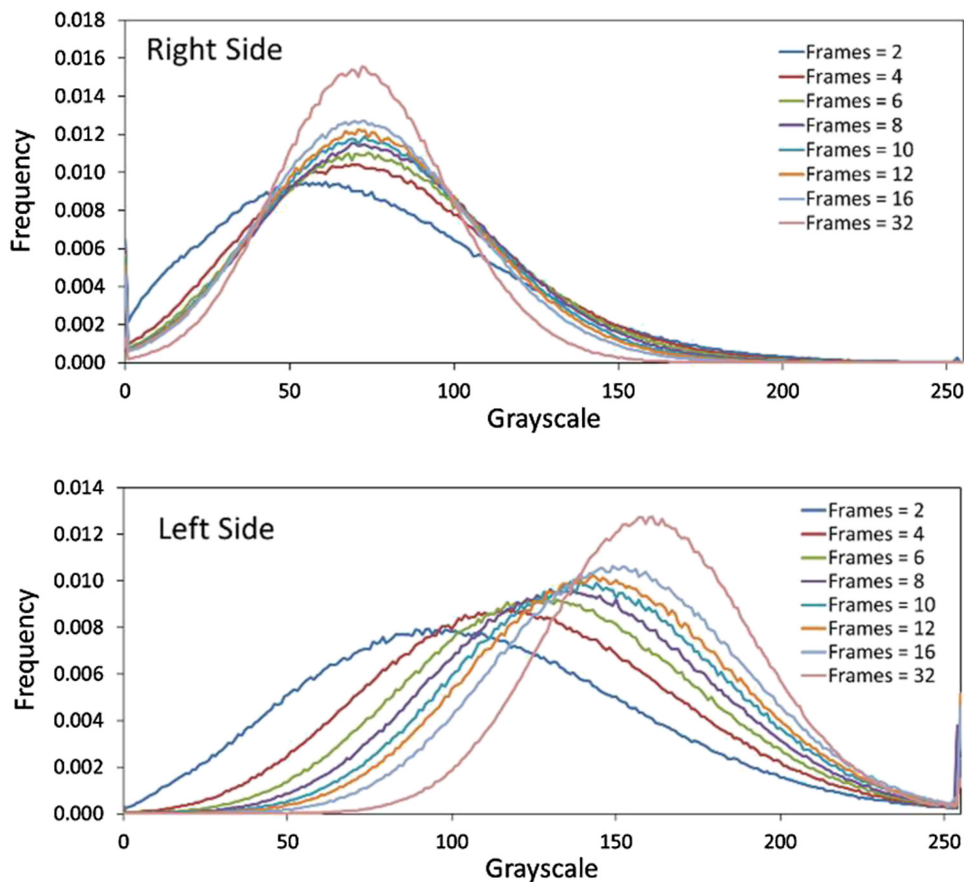


FIG. 4. Histograms of the grayscale values of the right and left sides of the isolated edge experimental SEM images as a function of the number of frames of averaging.

amount of noise in the image. Second, as the noise in the image increases, the scaling reduces the noise range to fit into the 0–255 grayscale range but in doing so makes the signal range smaller. For the isolated edge case, this means that the ratio of the mean grayscale values of the left side to the right side (a material contrast) is highest at 32 frames of averaging (2.21), but goes down as the number of frames decreases (to 1.46 at 2 frames). The implications of this scaling strategy will be discussed below.

This scaling strategy is also seen in a set of images of line/space patterns as a function of the number of frames of averaging. In Fig. 6, average linescan plots of 32-nm pitch line/space images (after etch) are shown as a function of the number of frames of averaging. Due to the grayscale scaling strategy employed by this CD-SEM, the increased noise of the lower number of frames is transformed into a decreased signal at a more constant level of noise. If the 32 frame average linescan case is taken as an estimate of the actual signal, the higher noise cases can be derived from the "actual signal" by multiplying by a scale factor, then shifting to a higher grayscale value by adding an offset. The resulting scale and shift factors are shown in Fig. 7, determined as the values that must be applied to the 32 frame linescan to provide the best match to the other linescans.

As further evidence of the proposed scaling strategy, it was observed that the 32 frame and 24 frame images for these 32 nm pitch line/space patterns did not exhibit a noticeable number of pixels clipped at 255. For the 16 frame images, there were about 0.15% of the pixels at a grayscale level of 255, and for 12 and lower frames, each image showed about 0.3% of the pixels at 255.

The scaling observed for the signal also applies to the noise. The same images used to extract the average linescans shown in Fig. 6 were used to measure the grayscale noise as a function of the number of frames of averaging. The grayscale noise was measured as the average of the standard deviations of each column of pixels in the image, avoiding the regions near the line edges. As seen in Fig. 8, the "as measured" noise does not follow the expected $1/\sqrt{N}$ trend due to the scaling of the grayscale levels of the image. However, by rescaling the measured noise by dividing by the scale factor as determined from the average linescans and given in Fig. 7(a), the expected statistical behavior of the noise is recovered. This allows us to generate a grayscale noise model from these experimental SEM images prior to the grayscale scaling step,

$$\sigma_{GN} = \frac{\sigma_{SFGN}}{\sqrt{\# Frames}}, \tag{3}$$

where σ_{SFGN} is the single-frame grayscale noise (without scaling), equal to 108 for this data set. While Eq. (3) is for

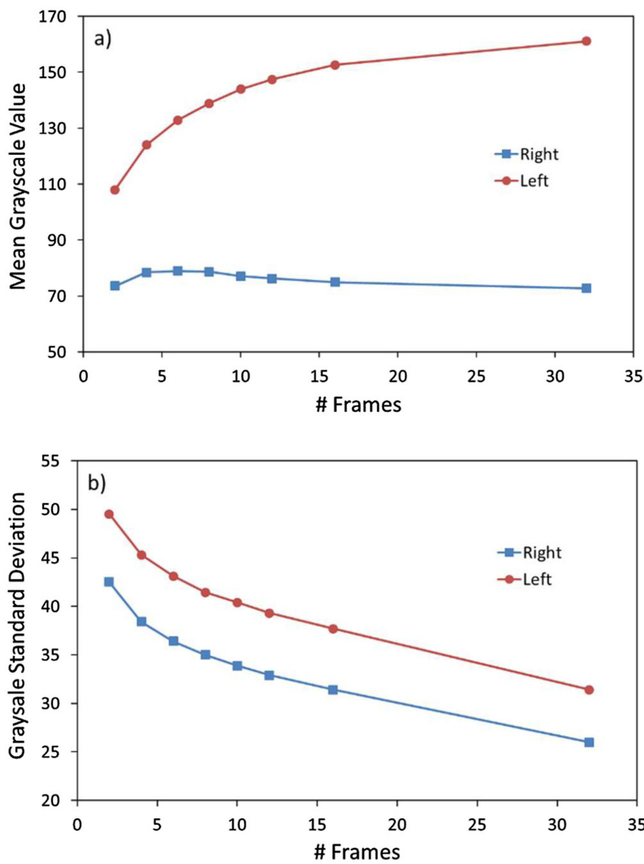


FIG. 5. Analysis of the data from Fig. 4 showing (a) the mean grayscale value and (b) the standard deviation of grayscale values for the left and right sides of the isolated edge features.

the 800 V after-etch data, a very similar result was obtained for 500 V after-development images of photoresist lines. For that case, the single-frame grayscale noise in Eq. (3) is changed from 108 to 141.

From Fig. 7, it appears that the grayscale scaling and the grayscale shift track each other. In fact, they are approximately related by

$$Shift = 75(1 - scale). \tag{4}$$

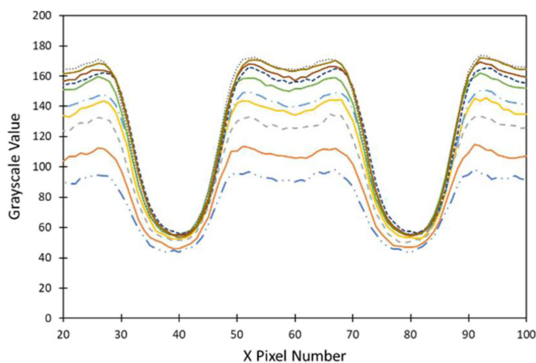


FIG. 6. Average linescans (the average of all pixels in the y-direction) for 32 nm line space patterns (after etch, Hitachi CG5000 CD-SEM, 800 V, 0.8 nm square pixels) as a function of the number of frames of averaging.

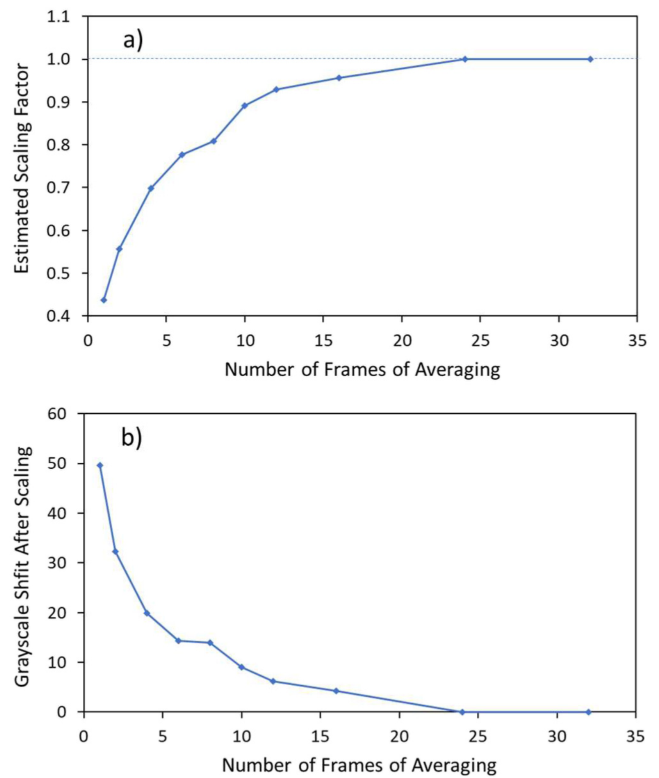


FIG. 7. For the data in Fig. 6, the estimated (a) scaling and (b) grayscale shift up after scaling required to turn the 32 frame average linescan into the other linescans as a function of the number of frames.

Combining the shift and scale together gives a conversion from the low-noise (unscaled) signal G_{32} to the noisy (scaled) signal G_N,

$$\begin{aligned} G_N &= scale \times G_{32} + 75(1 - scale) \\ &= scale \times (G_{32} - 75) + 75. \end{aligned} \tag{5}$$

The reason for the shift is unclear, but the reason for the scale comes from the need to keep the grayscale values between 0 and 255, as discussed above.

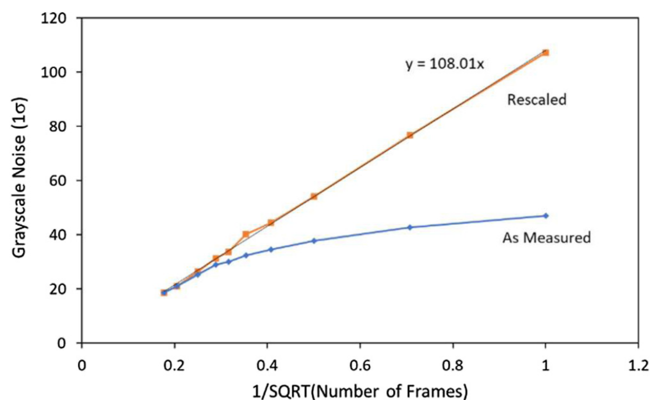
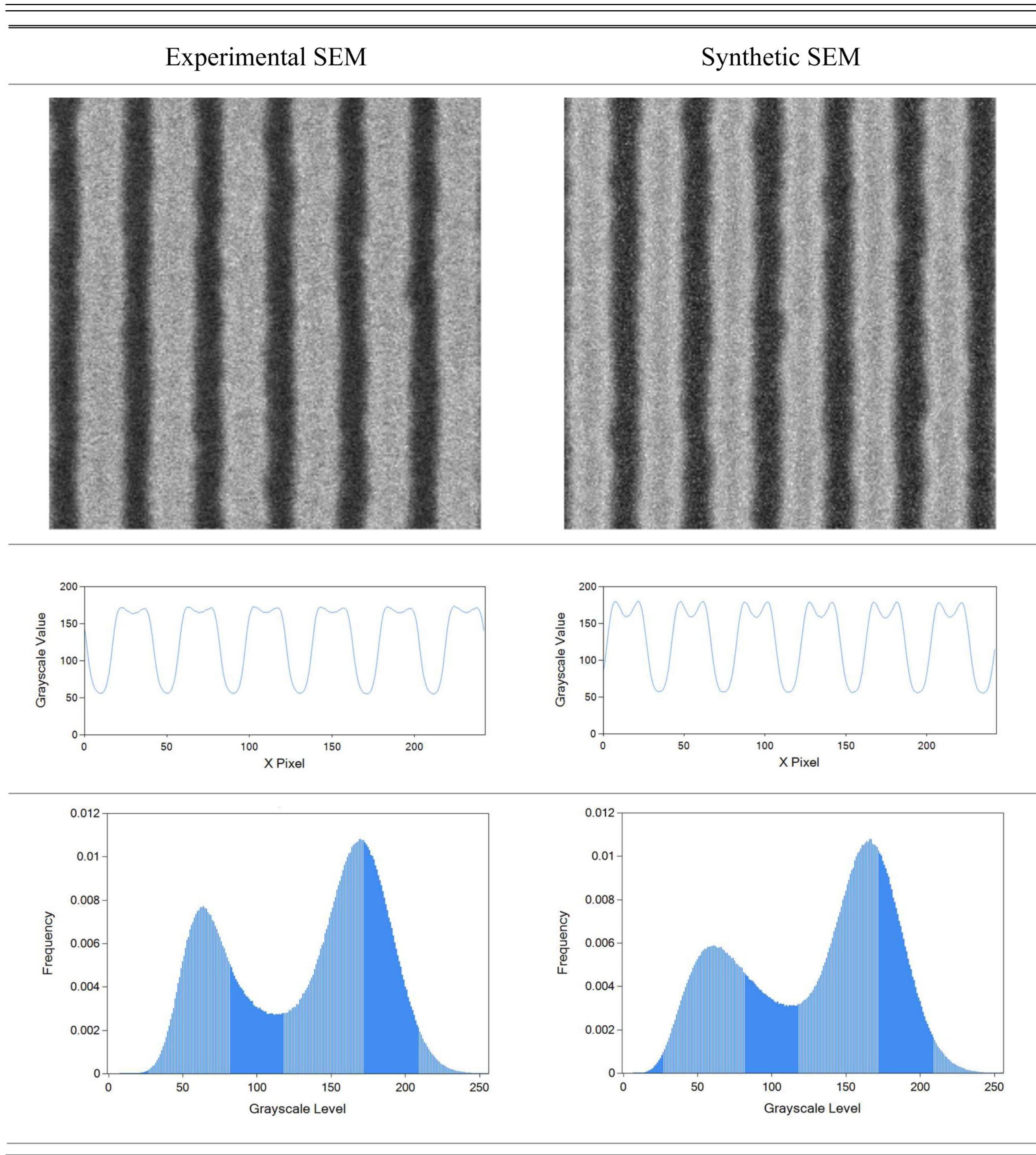


FIG. 8. For the same images that produced the average linescans shown in Fig. 6, the grayscale noise was calculated as the average standard deviation of each column of pixels, avoiding the regions near the line edge. This "as measured" grayscale noise was then rescaled by dividing by the scaling factor found in Fig. 7(a).

TABLE I. Comparison of experimental and synthetic SEM images for the after-etch case with 32 frames (linewidth = 20 nm, pitch = 32 nm, pixel size = 0.8 nm).



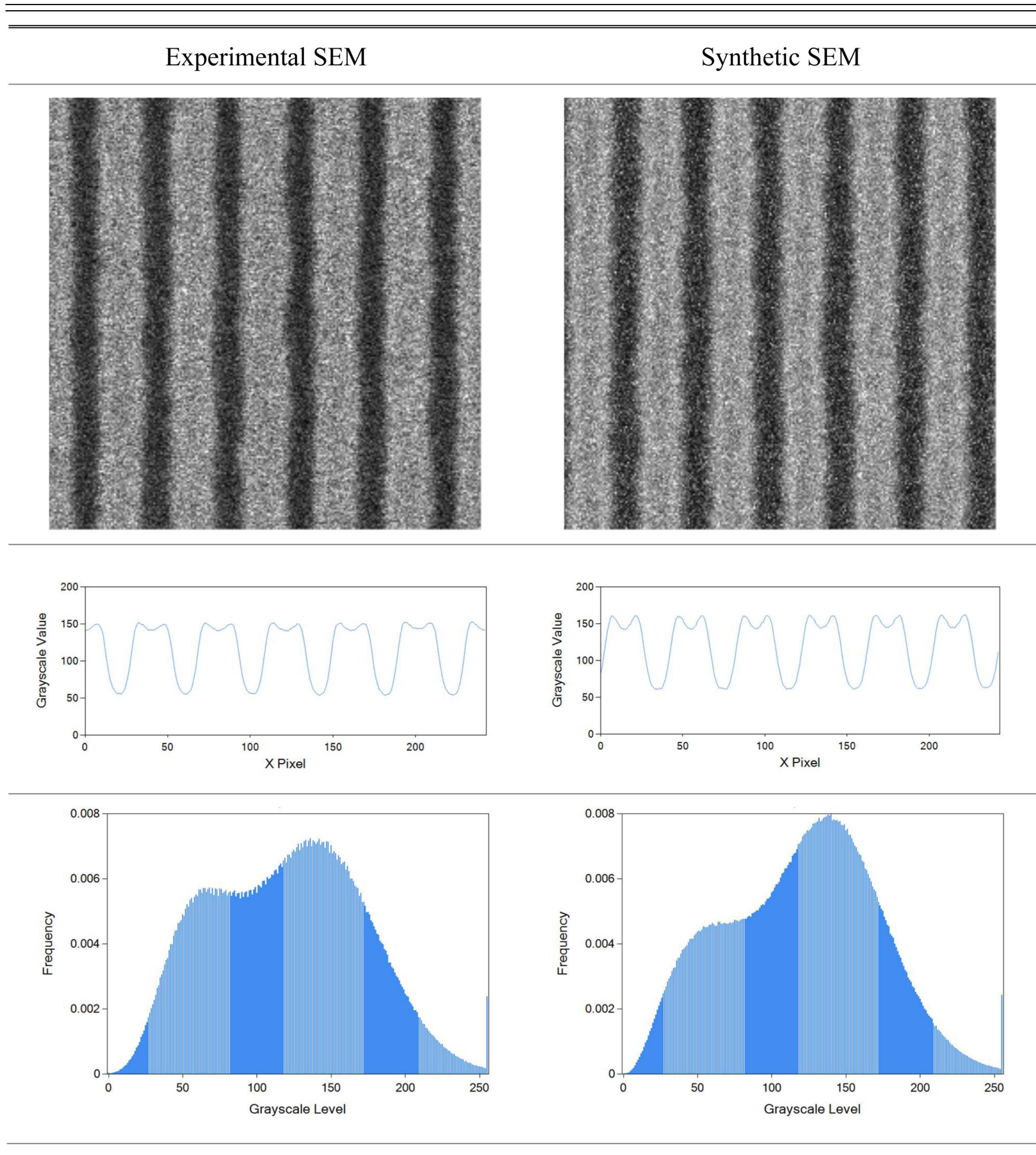
IV. GENERATING REALISTIC SYNTHETIC SEM IMAGES

The analysis of experimental CD-SEM images of various features as a function of the number of frames of averaging as described above can be used to define a method for generating synthetic SEM images that not only mimic the average linescan behavior of the images but also the noise behavior. The full process is as follows:

Step 1. Generate feature edges with predetermined statistical roughness by specifying the mean linewidth and pitch, the 1σ LER, the correlation length, the roughness exponent, and the correlation between edges.

Step 2 (optional). If desired, beam position error can be added to the output of step 1 by adding a random edge deviation from a Gaussian random number of mean zero and specified standard deviation.

Table II. Comparison of experimental and synthetic SEM images for the after-etch case with 8 frames (linewidth = 20 nm, pitch = 32 nm, pixel size = 0.8 nm).

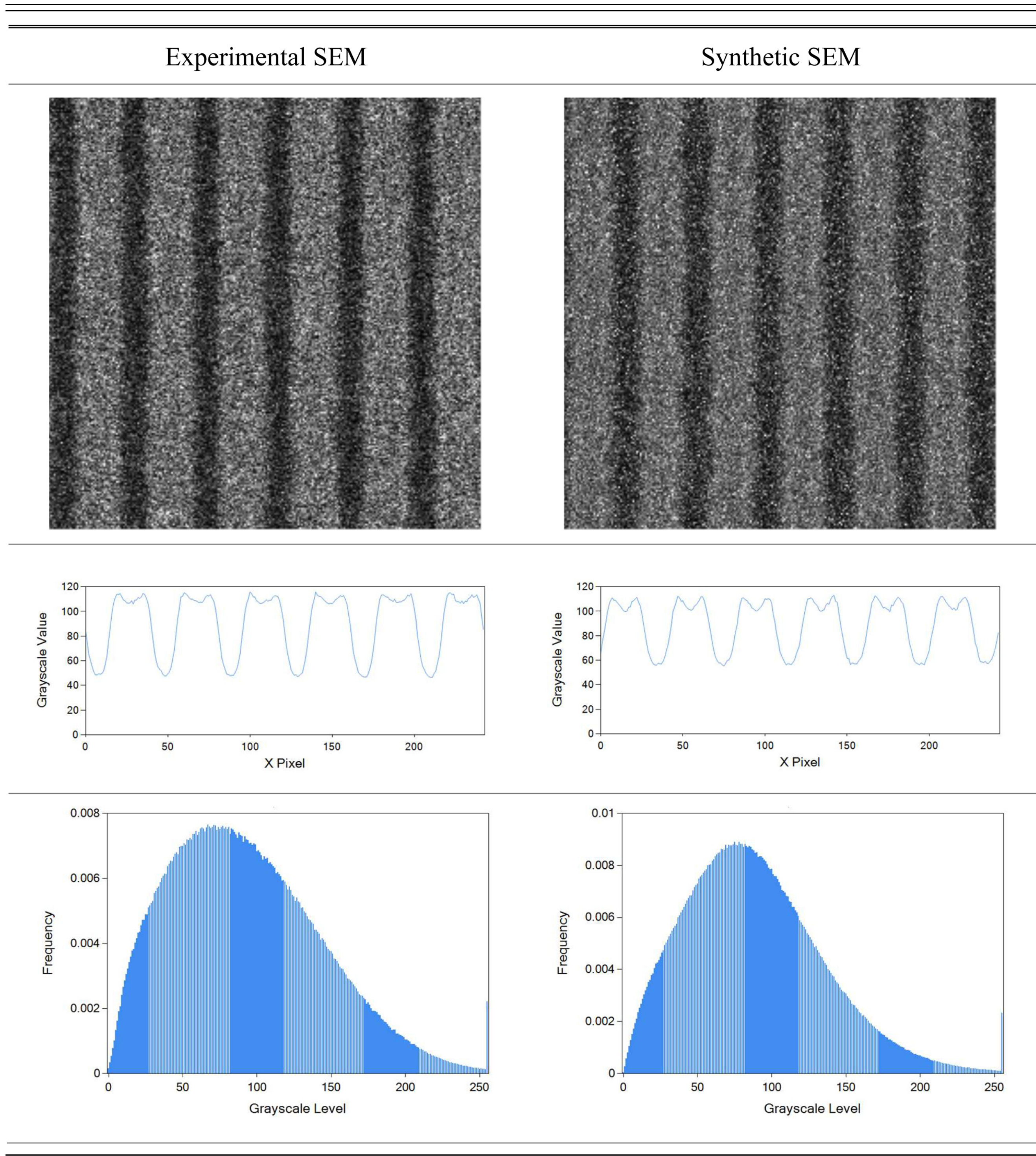


Step 3. Convert these edges to a noise-free synthetic SEM image using, for example, the Analytical Linescan Model. The output is a grayscale image with grayscale values in the range of 0–255, but with actual grayscale values typically between 50 and 200.

Step 4. Add noise to the output of step 3 by changing each pixel's grayscale value to a Gamma-distributed random number with the mode of the distribution equal to the noise-free grayscale value and the standard deviation of the distribution given by Eq. (3).

Step 5. Scale the image if necessary. Check to see if more than 0.3% of the pixels have values that equal or exceed 255, and if so, scale down all the image grayscale values until at most 0.3% of the pixels are at 255 or greater. Finally, clip any pixel values greater than 255 to be 255.

TABLE III. Comparison of experimental and synthetic SEM images for the after-etch case with 2 frames (linewidth = 20 nm, pitch = 32 nm, pixel size = 0.8 nm).



This process was used to generate synthetic SEMs for comparison to experimental SEMs collected as a function of the number of frames of averaging in the SEM. Results are presented in Tables I–III. Since no attempt was made to calibrate the Analytical Linescan Model to the actual materials used in the experiment, the average linescans do not match exactly. However, the results are close enough to test out the noise model being employed. As seen from the grayscale histograms for 2, 8, and 32 frames, the synthetic SEM images match the noise behavior of the experimental images quite closely.

V. CONCLUSIONS

In order to study the ultimate limits of line-edge roughness metrology using scanning electron microscopes, a

useful tool is the closed-loop simulation experiment of generating synthetic SEM images of known feature roughness and then measuring those images as experimental data to compare the measured results with the known correct answers. In this way, the influence of nonideal behavior can be investigated. While this approach has been used in the past,[6] these prior works have generally assumed Gaussian distributions of pixel noise and noise levels that are small compared to the 255 range of grayscale values. When exploring the limits of line-edge roughness metrology, high levels of noise are needed and thus a more accurate model is needed for how noise enters the SEM signal and how the SEM scales the signal to fit within the 0–255 grayscale range.

This paper has proposed a noise model for SEM images that assumes image noise is Gamma distributed, with the mode of the distribution equal to the noise-free (ideal) signal value. This noise model also adds the important step of image scaling, lowering the magnitude of the signal in the presence of high-noise levels to keep the fraction of image pixels at or above 255 equal to a constant 0.3%. These details of the noise model have been verified by comparison to experimental SEM images as a function of the number of frames of averaging used.

These empirical observations have also detected a grayscale shift in experimental SEM images so that the zero baseline level of the image seems not to be fixed at zero emitted secondary electrons. The exact nature of this zero-shift of the gray scale has not been fully elucidated and so has not been included in the noise model to date.

Future work will use the new noise model to compare the measurement of synthetic SEM images to that of experimental SEM images and to elucidate the ultimate resolution of SEM-based unbiased roughness measurements.

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