Global minimization line-edge roughness analysis of top down SEM images

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Abstract

Line edge placement error is a limiting factor in multipatterning schemes which are required for advanced nodes in high volume manufacturing for the semiconductor industry. Thus, we aim to develop an approach which provides both a quantitative estimate of whether a segment of a feature edge is in the ideal location and a quantitative estimate of the long wavelength roughness. The method is described, numerical simulation models its application to the issue of distortion caused by SEM aberrations, and the method is applied to a sample data set of SEM images. We show that the method gives a robust estimate of a major component leading to feature edge placement error. Long wavelength distortions either from SEM aberrations or from long wavelength noise have a clear statistical signature. This methodology applied to a large, consistently acquired SEM data set allows estimates as to important elements required to assess the line edge placement error issue and to whether there is underlying long wavelength roughness which arises from physical sources.

Subject Terms: line-edge roughness, linewidth roughness, stochastic-induced roughness, LER, LWR, edge placement error

1. Introduction

The use of multi-patterning to achieve the feature sizes required for advanced nodes has increased the importance of determining edge placement error. We do not address here the overlay issue, but rather misplacement of features within a pattern of other features assuming that the global overlay error is independent of the errors we wish to quantify. We will concern ourselves for simplicity with patterns consisting of parallel line and spaces. A typical question one would like to answer is how well placed a particular segment of a line is compared to where it should be. Some of the measures that have been used to quantify the answer to this question are the mean and variance of the CD of the line whose edge we are considering. Another is to quantify the roughness of the edge itself, the line edge roughness (LER), which is often done by analyzing the squared modulus of the Fourier transform of the spatial line edge roughness (called the power spectral density, PSD).

Besides serving to answer the important commercial question of whether a particular pattern is close enough to the ideal pattern, this analysis can often point to the physical causes of the non-ideality. It is often found that the largest contributor to LER comes from long wavelength roughness, with wavelengths on the order of a large fraction of the frame size of scanning electron microscope (SEM) images which are typically used as the first step in the analysis of this problem. The long wavelength roughness is also the hardest roughness to correct with later processing steps. In this paper we propose an analysis method which quantifies roughness on this and longer scale lengths. We show that roughness can come from either instrument aberrations and is therefore spurious, can come from the cumulative effect of small scale length, locally independent random roughness, or can come from a physical source of long wavelength roughness. These sources each have different statistical signatures and can be separated from each other by examining a data set which is large and consistently obtained. We also show that this analysis method addresses the question: "is the line edge in the right place?", a question which is not directly addressed by other analysis methods. In this paper we detail the method of analysis, use simulations to analyze the signature of apparent long wavelength roughness which comes from instrumental aberrations, and then apply the method to the analysis of a set of SEM images taken from a sample line and space pattern.

2. Global error minimization motivation and method

Given a top down SEM image, we would like to estimate to what degree the underlying features deviate from the ideal. We will confine the study here for simplicity to regular patterns of features consisting of nominally parallel line and spaces. The analysis can proceed in progressive stages of refinement. We start by assuming that an edge detection algorithm has been used to detect the left and right edges of the features imaged by the SEM and has produced a set of $(x_i, y_i)^n$ arrays describing the position of the edge of the features in Cartesian coordinates determined by the SEM. Here $(x_i, y_i)^n$ are the x and y coordinates of a point on the n^{th} edge (indexed from the left of the image), on the i^{th} pixel row, the coordinates being relative to the lower left hand side of the SEM image. Typically the features will have edges which are approximately vertical, that is, parallel to the y-axis of the image.

The crudest and often the most useful analysis is to determine the statistics of the width of the lines: for each pixel row i we subtract the x_i values of the left from the right edges to give an estimate of the linewidth for a particular value of i. We then average over i to determine the average width $\langle x_{i\text{-}right} - x_{i\text{-}left} \rangle$, where the angular brackets mean an average over i for each feature. We can perform a further average over all the features in an SEM image which we denote by double brackets $\langle\langle\ \rangle\rangle$; in our previous terminology, this is an average over the index n. The resulting double average gives an estimate of what is often termed the critical dimension (CD) and if we assume that the individually determined widths are distributed in a Gaussian fashion we can estimate the standard deviation of that Gaussian. This procedure seeks to give an answer to the question: "how wide is the underlying feature, and what is the probability that the width will differ from the average value by a given amount?" The procedure gives an estimate as to this answer due to errors in the SEM imaging, the edge detection procedure, the fact that the lines are not vertical and the assumption that the widths at any point are distributed as a Gaussian characterized by two parameters: its mean and standard deviation.

We often wish to obtain some further information on the nature of the roughness of the underlying line and space features beyond the width of the presumed Gaussian distribution. By roughness we mean the departure of the line edge from its ideal position. Such information is of use in attempting to understand the cause of the roughness. It is also typically what one requires in order to estimate the impact of roughness on the electrical performance of the underlying features. For example, what we often require is the answer to the question: "what is the probability that the line width exceeds some amount for a particular length?"

The first step to such an understanding is to examine the statistics of the roughness of a single edge and this is typically done by performing a Fourier transform of the deviation of the line from its ideal position. One then examines the square of the modulus of the Fourier coefficients versus the inverse roughness wavelength; with appropriate normalization this is denoted the power spectral density (PSD). The PSD corresponding to each feature edge is then averaged together and often segregating into left and right edges (left and right defined by the scan direction of the SEM). Averaging the PSDs of the feature edges eliminates any information as to correlations between feature edges for any particular wavelength. In the crudest approach one takes for each feature edge the vector of x coordinates $\{x_i\}$ for that particular feature edge, and computes the Fourier transform of the vector $\{x_i - \langle x_i \rangle\}$ for a single line. The underlying assumption is that the ideal feature edge is vertical, that is parallel to the y axis of the SEM image. The set of ideal lines is defined for an image with n features by the set of average values $\langle x_i \rangle$ for each line, that is, $2n$

parameters define the model of the set of ideal lines. This is in fact an erroneous constraint since the orientation of the feature edges relative to the SEM scan frame is only approximate and depends either on the operator or on the automatic alignment hardware and software. This method introduces an artificial error which particularly affects the long wavelength roughness.

A better method of estimating the deviation of the feature edge as detected by the SEM from the ideal is to fit the best straight line to the detected edge by minimizing the squares of the residuals between the straight line and the $\{x_i, y_i\}$ array. Thus the minimization is performed on the sum of squares of the vector $\{x_i - (a+by_i)\}$ where a is the offset of the line from the left edge at the bottom of the image, and b is the slope of the line relative to the vertical with $b=0$ being vertical. For each feature edge this gives two fitting parameters, a and b, so for a complete image of m features each with two edges, there are m fitting parameters. The Fourier transform is performed on the vector of residuals $\{x_i - (a_{\min}+b_{\min}y_i)\}$ where $a_{\min}$ and $b_{\min}$ are the values of a and b which minimize the sum of squares. As before the squared modulus of the Fourier transform is averaged over all the lines in an image. This method circumvents the problem that the feature edges are not necessarily aligned with the y axis of the SEM image. The resulting PSD gives an answer to the question: "what is the probability that the detected edge is not straight and how much do different wavelengths contribute to this departure from straightness?" The maximum wavelength that can be estimated by this method is approximately the height of the image, although the windowing required due to the non-periodicity makes this somewhat more complex. We note that the total roughness which can be computed either by integrating the PSD over all spatial frequencies or by summing the squares of the deviations of the detected edge positions from the fitted straight lines is less than obtained from analysis in which the erroneous constraint is applied that the feature edges are aligned with the SEM frame. This is because we are fitting the data with a greater number of free parameters.

At this point in the analysis, however, we have left valuable *a priori* knowledge on the table. We have used the *a priori* knowledge that the underlying ideal feature edges are straight lines. This is based on a set of assumptions, the most obvious that the mask in fact was designed to have features which have straight lines, but also that the mask has errors which are smaller than any of the errors we are considering, and that there are no aberrations in the SEM imaging which would distort a straight line. We also, however, have the *a priori* knowledge that the underlying ideal feature edges are parallel to each other, again an obvious characteristic of line and space patterns. This constraint, that the ideal set of underlying feature edges are straight lines which are parallel, reduces the number of fitting parameters from $4n$ to $n+1$. This analysis is the first step to answering a somewhat different question from the previous questions; this question is: "are the feature edges in the right place?" This is clearly the key question if one wishes to predict future electrical properties.

Besides the fact that the feature edges are ideally parallel we also know for the assumed mask geometry that they all have the same pitch and that they all have the same width or CD, although due to various process details the CD may not be the intended or ideal CD. Adding these constraints reduces the number of fitting parameters to 4: the slope of the set of parallel lines, the pitch, the CD, and the position of some arbitrary feature such as the x coordinate of the bottom of the left most line. Ideally we also know the pitch *a priori*, however errors in the SEM magnification calibration would mislead us into erroneously attributing error to the features. In fact, the fitted pitch may be the best estimate as to the actual SEM magnification. Naturally, since we have reduced the number of fitting parameters to 4, the estimated roughness increases. Notice that this estimate of the roughness is neither more or less correct that the estimate using individually fitted straight lines, they are answering different questions.

At this point we have used all the *a priori* knowledge available to us. By examining the deviation of the detected feature edges from a set of parallel, equal pitched, equally wide ideal features we are answering the question: “Is a particular feature edge in the right place?” Put more quantitatively, we can estimate the answer to the question: “what is the probability that a segment of a feature edge lies outside of a given distance from where it should be?” We have denoted this method for reference as the global minimization method which is shorthand for the global minimization of error given the constraints of parallelism, equal pitch, and equal CD. We now turn to some of the practical consequences of this model.

Applications of the global minimization method – aberrations and long wavelength roughness

Besides giving a more accurate assessment of whether a segment of a line is in the correct location, the global minimization method gives a way of estimating the effects of SEM aberrations and roughness whose wavelength is comparable to or longer than the SEM frame size.

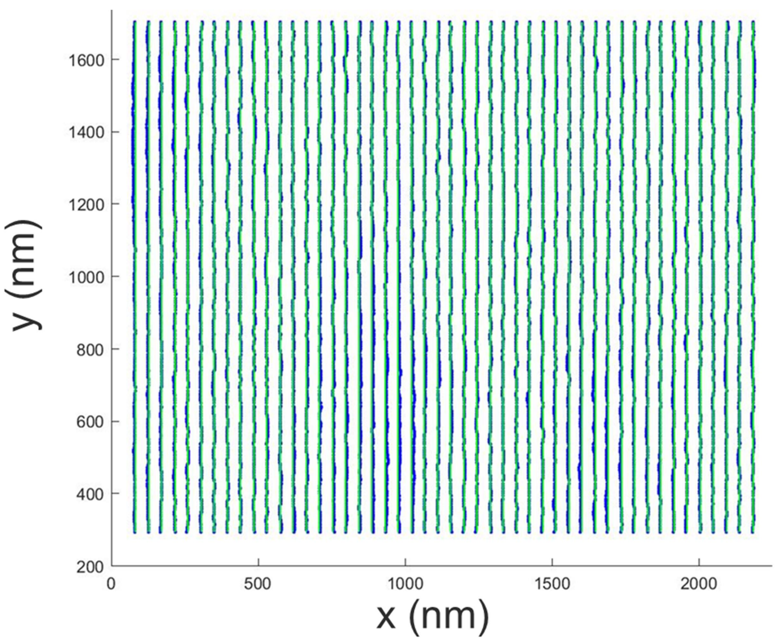


Figure 1. Detected line edges from an SEM image together with the set of ideal edges determined by the global minimization algorithm.

We show in Figure 1 a set of detected edge locations and the set of lines fitted using the global minimization algorithm. We show in Figure 2 for the left edges of these lines, the mean deviation of each line from its ideal location as a function of line index. One item is striking in this graph: the deviations of each line edge from its expected location appears to follow a pattern instead of being random. This deviation can be due to either an SEM aberration or to long wavelength roughness. It is not possible to distinguish between these two in a single image, but it is possible by considering a set of images of varying locations in the same line and space field. We would expect that the mean, averaged over images, of each line edge would have a distinct pattern in the case of SEM aberrations. In the absence of aberrations, the average of the mean deviation of a particular line edge index over many images should vanish. In addition, the magnitude of the scatter from image to image allows us clues as to physical nature of the long wavelength roughness. We expect long wavelength roughness to arise naturally from locally independent, random processes. Ignoring the correlation provided by resist blur (such as acid diffusion) since it affects a shorter wavelength, we can imagine that all roughness is due to random variations in the photochemistry and photon counts which are independent from point to point on the line edge. Such roughness, averaged over many images, will have equal amplitude Fourier components at all frequencies since it has no characteristic scale length. We therefore we expect that there is roughness on scale lengths greater than the frame size although we cannot measure it directly on any one single line edge. However, we can extrapolate the roughness that is measured at wavelengths which are accessible in the SEM image to longer wavelengths since the spectral density is constant for such a process. If the roughness which is estimated by examining the scatter from image to image is larger than this, then this indicates there are physical processes which are generating long wavelength roughness which go beyond the cumulative effects of independent local random processes. These are important because they can point to physical causes which can be addressed directly.

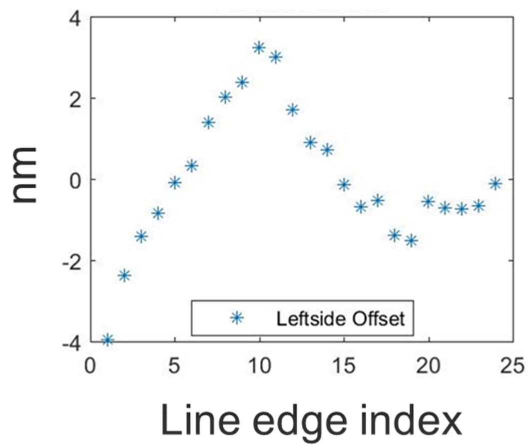


Figure 2. Mean offsets of lines from their ideal locations as a function of line edge index for the left edges of Figure 1.

The residuals between the expected and the actual locations of the lines can also be examined for correlations between lines. This gives a quantitative answer to the question: is there a pattern to the residuals? More specifically we would ask whether there was a correlation in the residuals between adjoining lines. We would certainly expect this if there are aberrations present whose scale length is larger than the line spacing. We would not expect a correlation between the residuals of adjacent lines in the case of long wavelength roughness generated by locally independent random processes. However, we would expect a correlation for long wavelength roughness due to physical causes with a longer length scale than the frame size. For example, consider the case that the long wavelength roughness is caused by tipping of the lines due to unbalanced surface tensions. If there was a gradient in some resist quantity which affected the mechanical stresses or strength of the lines and which had a component perpendicular to the lines, then we would expect adjacent lines to tip in the same direction if the gradient scale length is comparable or somewhat larger than the interline spacing. Very long gradient scale lengths will cause a uniform tipping of all the lines and scale lengths which are short compared to the inter line spacing will not cause an interline correlation. Notice that although we would expect an interline correlation of residuals in the case of long wavelength roughness caused by some physical mechanism such as the mechanical stress gradient, in looking at a given line, its residual would have a mean of zero in the absence of aberrations. On the other hand, aberrations will have both a finite mean for a particular line position and finite interline correlation.

We consider now some of the aberrations that we might expect. The first is a simple case in which the magnification is constant vertically, but varies horizontally. This would for example produce closely spaced lines on one side of the image relative to the other. This would give a set of residuals for the position of the lines which varied linearly as a function of line position. This aberration will not affect the PSDs which are calculated from the residuals (see below), since they do not include the zero frequency component and therefore are insensitive to a constant offset, but would be visible in examining data such as shown in Figure 2 for a number of images.

Another aberration is that the magnification is uniform horizontally, but varies from the top to the bottom of the image, the so-called keystone or trapezoidal distortion. This is important because such an aberration gives the same signature as roughness whose wavelength is on the order of or longer than the image height. The PSDs which we will calculate below are performed on the residual departure of the detected edged from the ideal edge location and by the nature of the aberration will have a spurious linear trend which will contribute strongly to the low frequency components. We give an explicit example of that below. The trapezoidal distortion can be detected by fitting the residuals left from the global minimization process to straight lines and considering the slope of these lines as a function of line position. A trapezoidal distortion will result in a non-zero mean for the fitted slopes and an approximately linear progression of slope horizontally across the SEM image field. We note that applying a linear detrending for each edge individually will eliminate the spurious linear offset in the residual if there is trapezoidal aberration, however, it will also eliminate non-spurious linear offsets from longer wavelength roughness and give a falsely optimistic estimate of the roughness.

3. Simulations

An important aspect of the global minimization approach is that it allows an approach to quantifying long wavelength departures from the ideal pattern. We explore this here by considering the effect of such departures caused by SEM distortion during the image formation process through the use of simulation. We assume here that there is an imaging aberration which is constant in time and is the same if one moves from one field to another in a pattern. A simulated set of randomly rough features can be distorted with a known image field distortion function, then analyzed in the same way that an experimental set of features would be. Comparisons of the power spectral density (PSD) functions with and without these distortions will provide insight into the experimental measurements described below. Simulations were performed using MetroLER v1.0 (Fractilia, LLC). A method for generating randomly rough features with a given power spectral density behavior has been previously described.[1] This method was used to simulate rough edges, creating instantiations of a zero-mean random edge that follows a predefined power spectral density. Placing these edges together to form a set of features, a simulated "image" is created, mimicking the results of edge detection by the SEM. Thousands of simulations were run and the results averaged to obtain the expected PSDs.

We define the statistical behavior of the rough edge using a model of the power spectral density (PSD). For example, most LER/LWR data have been found to be well described by the Palasantzas power spectral density function:[2]

$$PSD(f) = \frac{PSD(0)}{\left[1 + (2\pi f \xi)^2\right]^{H+1/2}} \tag{1}$$

where σ^2 is the true variance of the line edge/linewidth, ξ is the correlation length, H is the Hurst roughness exponent, and PSD(0) is calculated (using the gamma function, Γ) by

$$PSD(0) = 2\sigma^2 \xi \left(\frac{\sqrt{\pi}\,\Gamma\left(H + \frac{1}{2}\right)}{\Gamma(H)} \right) \quad (2)$$

Collections of feature edges form a single "image", as shown in Figure 3. In this case, every edge was assumed to be uncorrelated with the other edges. In calculating the PSD's we first apply the global minimization procedure and then apply a Fourier transform to the residuals; the square of the modulus of the components of this Fourier transform then give the PSD's which are plotted. In the case of no imposed SEM image aberrations, the randomly generated rough features have a zero mean, that is their average over many images converges to the ideal set of equal pitch, equal width, parallel lines. This gives a PSD shown in Figure (3)

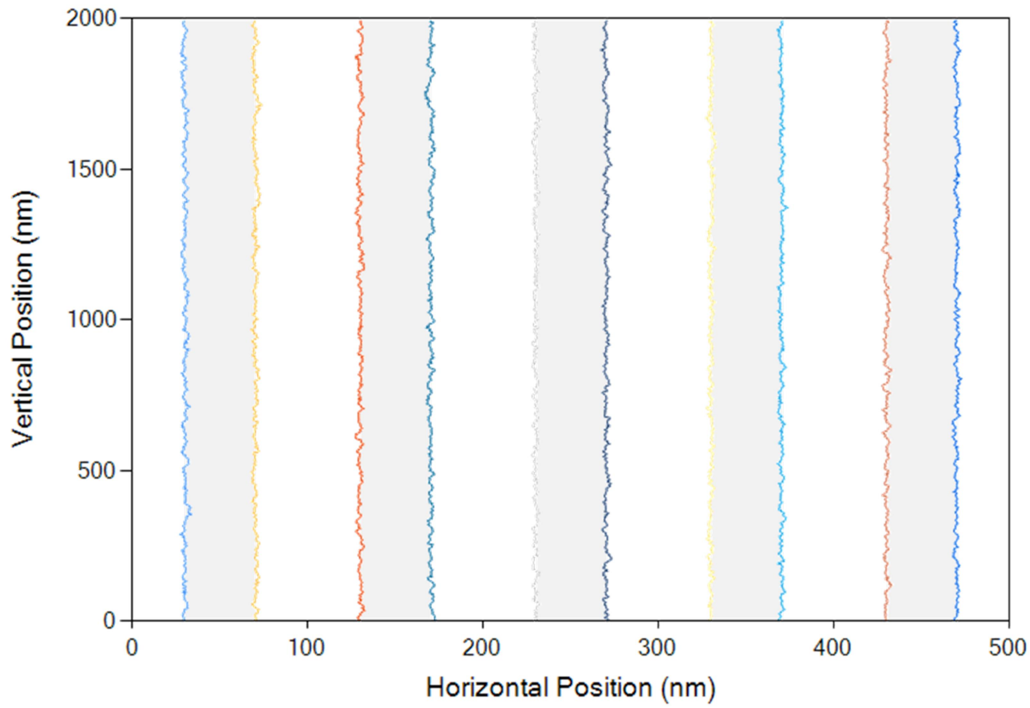
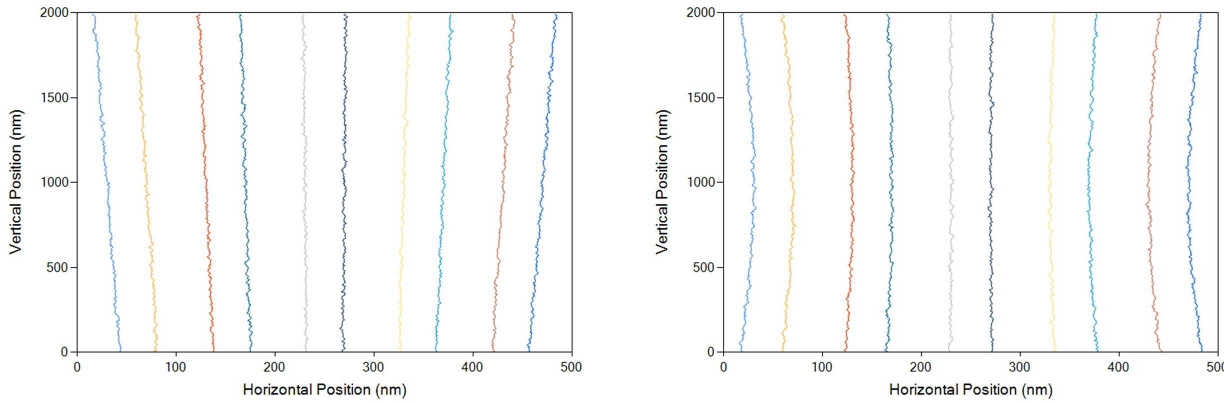


Figure 3. A collection of five simulated features, nominally 40 nm in width with a pitch of 100 nm, with roughness having σ_{LER} = 1 nm, correlation length ξ = 10 nm, and roughness exponent H = 0.5.

From this base, field distortions can be added. While actual image field distortions in well-corrected SEMs are expected to be complex, here we will use two simple distortion models: trapezoidal distortion and pincushion (barrel) distortion and their combination. Figure 4 shows examples where these distortions were added (the magnitudes of the distortions added were at least one order of magnitude larger than should be expected in order to make this figure easier to visualize and interpret). Both the trapezoidal distortion coefficient and the pincushion distortion coefficient represent the maximum x-position error at the four corners of the field (with no error at a y-position corresponding to the middle of the field).



(a) (b)

Figure 4. Example images using the same features as in Figure 3, but with added field distortions: (a) trapezoidal distortion of +15 nm, and (b) pincushion distortion of +15 nm.

Using these generated rough features within a field, the data was analyzed in the same way as an experimental SEM image, and PSDs were generated. For the simulations that follow, 400 y-pixels of 5 nm each produced 2-μm long lines. Ten 40-nm lines on a 100 nm pitch were placed in each image, so that the width of the image field was 1 μm. The roughness parameters were σ_{LER} = 1 nm, ξ = 10 nm, and H = 0.5. The metrology was simulated by assuming a Gaussian metrology probe averaging width (FWHM) of 5 nm and 1-sigma metrology noise of 0.5 nm.[3,4] The resulting PSDs (the average of 1000 images) are shown in Figure 5 for linewidth roughness (LWR), line-edge roughness (LER), and pattern placement roughness (PPR, the average of the left and right edges of a line) for the case that there are no systematic distortions. In generating the PSD's displayed in the following figures, the PSD's of each line edge from each image are averaged together.

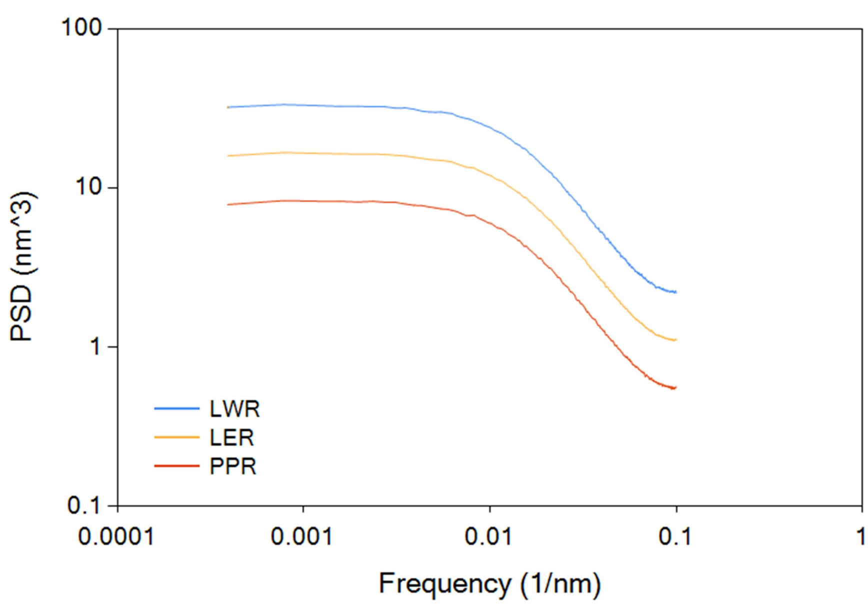
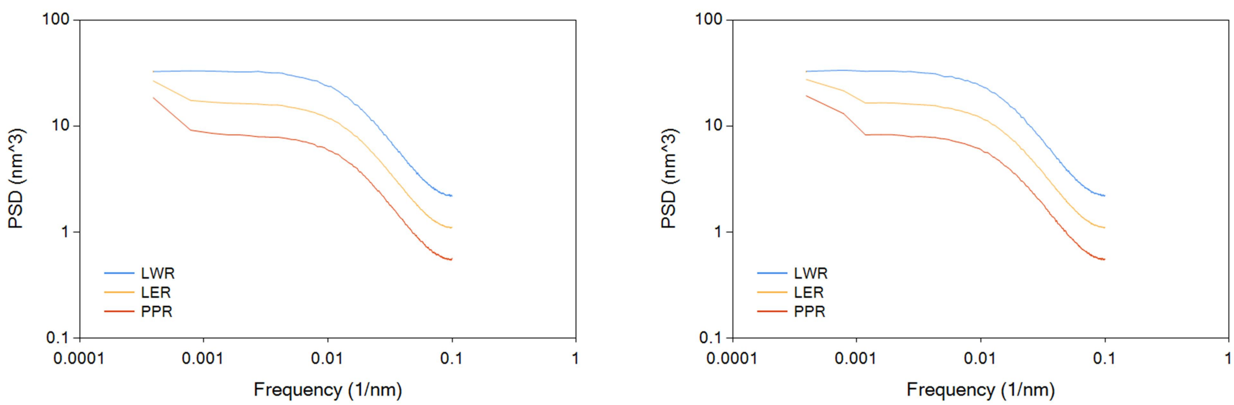


Figure 5. Power spectral densities (PSD) for 1000 simulated images, each with 10 features (40-nm line on a 100-nm pitch) that are 2000-nm long (400 pixels of 5-nm size). Roughness parameters were σ_{LER} = 1 nm, ξ = 10

nm, and H = 0.5, and non-ideal metrology assumed a Gaussian probe width of 5 nm and metrology noise of 0.5 nm.

Adding a trapezoidal distortion as shown in Figure (4a) is equivalent to adding a linear function to the residuals. The function varies linearly with height on the image and the slope of the linear function increases linearly as one moves horizontally left to right. For a particular line position on the image, this added function is the same for every image. Thus the Fourier transform of this linear function is a constant from image to image. When added to the Fourier transform of the randomly generated zero mean roughness and the modulus of the sum squared and averaged over images the net effect is to add the PSD of a sloped straight line to the PSD shown in Figure (5). This PSD scales as $1/f^2$ and its effect is felt most strongly at low spatial frequencies. This is seen in Figure (6a) .A pin cushion distortion can be analyzed in a similar fashion. Notice that one would expect the PSD for particular line positions in the image to exhibit different behaviours: for the pin cushion and trapezoidal distortions the PSD for the line near the image center averaged over images, will have less low frequency distortion than lines near the image edge. For both distortions LWR is hardly affected, since it is based on the difference between nearby edges that are mostly affected the same by the distortion. Figure 6 shows the results of adding small amounts of field distortion: 0.5 nm of trapezoidal error in Fig. 6(a) and 1.0 nm of pincushion error in Fig. 6(b). As can be seen, even small amounts of SEM image field distortion cause noticeable increases in the measured low-frequency behavior of LER and PPR. For the trapezoidal first-order distortion, mostly the lowest frequency is impacted. For the pincushion second-order distortion, the lowest two frequencies are raised. Higher-order distortion terms will undoubtedly extend the rise in LER and PPR further in frequency.



(a) (b)

Figure 6. Resulting PSDs using the same simulation conditions as in Figure 5, but with added field distortions: (a) trapezoidal distortion of +0.5 nm, and (b) pincushion distortion of +1.0 nm.

Real, complex imaging systems are likely to have non-parametric distortions. Temporal drift can cause errors in the beam position from the start to the end of the scan, while spatial distortion can be caused by electromagnetic interference either with the beam itself, or with the deflection coils that control its position. The characteristic sign of field distortion is then expected to be a low-frequency rise in the LER and PPR that is not seen in the LWR.

The analysis thus far has been for time independent distortions due to SEM aberrations. Low frequency distortions to the spectrum can also come from zero mean random roughness with wavelengths longer than the frame size or from time dependent SEM aberrations. We can see this simply by extending the trapezoidal distortion in such a way that the distortion was random from image to image in magnitude and sign. In this case the Fourier transform of a particular line position will be the Fourier transform of the zero mean randomly generated roughness summed with the Fourier transform of a linear function with a random, zero mean coefficient. The PSD of this combination will be the PSD of the zero mean randomly generated roughness plus the modulus squared of a linear function multiplied by the variance of the random coefficient. This will appear on a PSD plot as an increase in low frequency roughness in the same way that an SEM abherration would although it will not vary from line position to line position.

The conclusion of the simulation study is that the rise in the low frequency components of the PSD for LER while not for LWR is an indication of long wavelength roughness coming either from SEM aberrations or from long wavelength roughness.

4. Experimental Results

We analyzed a set of 22 SEM images taken with a Hitachi 4800. These differ in many ways from conventional CD-SEM images. The beam energy is 15 kV, considerably higher than a conventional CD-SEM instrument. Each image is taken at one location and the imaging field moved by hand so that another field within the same line and space pattern was imaged. Some amount of re-focusing is required from field to field. The line and space pattern is from an internal test pattern with nominally 45 nm wide lines on 90 nm pitch. The sample was oriented so that the view is down onto the sample with the patterned lines oriented perpendicular to the left right scan direction. The coupon was partially processed so that the photoresist line pattern was transferred into a thin layer of silicon containing anti-reflection coating (SiARC). Photoresist was left at the end of the step on top of the SiARC. The magnification for the images is 50k. We note that these images differ from images taken with a CD-SEM, however, we are looking here to verify the general analysis method rather than to assess a particular photoresist or processing method.

MetroLER was used to analyze the resulting SEM images (x and y pixel sizes were 2.06 nm; the analyzed region was 1280x850 pixels). The analytical linescan model (ALM) was used to detect edges with no image filtering applied (see Figure 7). PSDs were calculated using the global minimization approach described above. Figure 8 shows the PSDs averaged from 22 images. The low-frequency behavior exhibits evidence of long wave length distortion possibly from SEM field distortion as discussed in the previous section. There is also an anomalous spike in the PSDs at a frequency of 0.204 nm^{-1} (compared to the Nyquist frequency of 0.2427 nm^{-1}). The origin of this spike is unclear.

Figure 9 shows the average measured pitch as a function of field position for the 28 lines in each image. This was obtained by measuring the pitch between specific line positions in the image and averaging over the 22 images. We would expect that for a time constant SEM aberration the measured pitch would follow a smooth variation with horizontal field position. We would have expected image to image scatter to be caused by long wavelength roughness given by extrapolating the measured PSD of the PPR to long wavelengths using the flat part of the PSD curve above a spatial frequency of 0.002 1/nm. However, No obvious trend is detected, indicating that a higher-order variation is likely at work in the time constant aberrrations. However, the error bars are quite large, given that 22 images were averaged together, indicating less than ideal magnification control for this SEM or indicating that there is a source of random roughness at spatial wavelengths longer than the frame size.

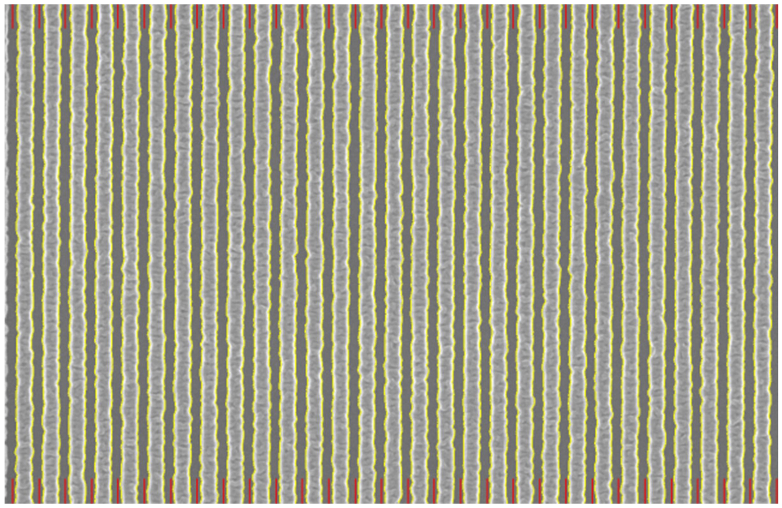


Figure 7. Example SEM image of 45 nm lines and spaces with detected edges shown in yellow (*x* and *y* pixel sizes were 2.06 nm; the analyzed region was 1280x850 pixels).

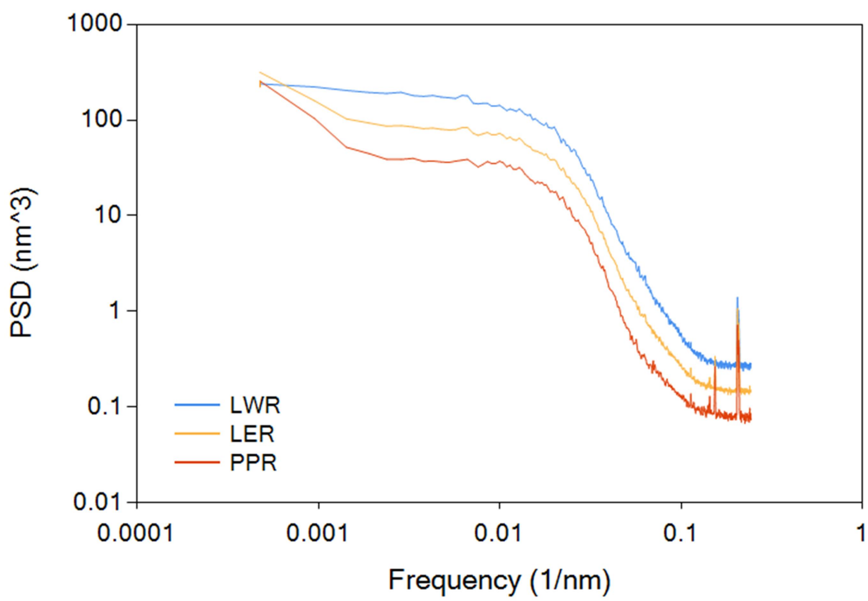


Figure 8. PSDs averaged for 22 images like the one in Figure 5, for a total of 623 features and 1246 edges.

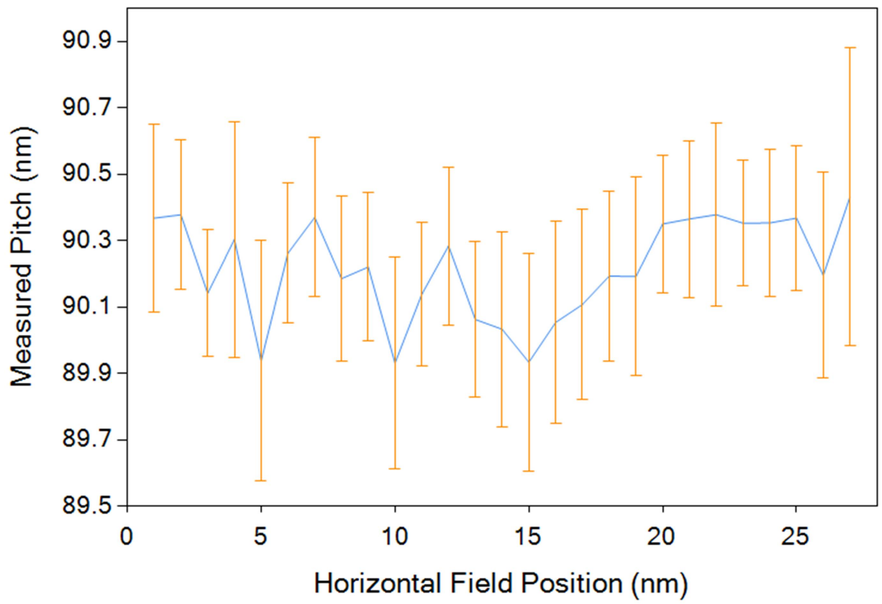


Figure 9. The average pitch for the 22 images as a function of horizontal field position for the 28 lines in each image. Error bars represent ±2 standard errors.

We conclude from this preliminary study that an image data set is required which is both sufficiently large and consistent from image to image. These requirements are satisfied by CD-SEM instruments.

5. Conclusions

We present here a method for the analysis of a set of top down SEM images of a pattern of lines and spaces taken from a particular CD – pitch region of a test pattern. We use the a prior knowledge that the ideal set of lines and spaces are parallel and have the same pitch and width (CD) in order to constrain the fitting procedure. By so doing, we give an estimate to the answer to the question: is the line edge in the right place? From a yield perspective, this is a key question. We also show that by looking at the PSDs and by the statistics of the departures of the detected line edges from the ideal position of the line edges we can begin to estimate the nature of roughness with a scale length longer than the frame size. Such roughness can be systematic (and constant in time) coming from SEM imaging aberrations and this technique can be used to diagnose these aberrations. It may also come from random long wavelength roughness due to physical or statistical randomness with scale lengths longer than the frame size. Quantifying such long wavelength roughness is the first step to remediating it.

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