# Reduction of Metrology Error for Line-Edge Roughness Measurement from Low-Dose SEM Images

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The measurement of line-edge roughness (LER) is important for understanding and controlling the performance of current and future semiconductor devices. The scanning electron microscope (SEM) is a standard tool for measuring LER. In this work we focus upon low-dose SEM images because they can be acquired relatively quickly and with less chance of resist shrinkage[2]. However, they also suffer from low signal-to-noise ratios (SNRs), which can lead to a large bias in LER measurement. This problem has been recently addressed using model fitting[2] and a standard image denoising technique[3]. We propose a new approach motivated by known features of the LER spectrum estimation problem. The power spectrum of the measured LER data differs from the true power spectrum of LER by a constant $S_{noise}$[4,5]. We consider the estimation of $S_{noise}$, and as a first step, use that estimate to approximate the true LER of rough lines.

We estimate $S_{noise}$ based on three factors which potentially contribute to metrology errors. The first one is the SEM signal profile[2] of the linescan of an isolated edge in the absence of noise. We use the SEM simulator JMONSEL[6] and a smoothing spline technique[7] to generate a continuous profile with the parameters suggested by Bunday and Mack[8]. A noiseless image with a rough or straight edge corresponds to 2048 of these SEM signal profiles. The next factor is the SNR of a SEM image, which can be computed[9]. We corrupt a noiseless image with randomly generated Poisson noise to obtain a noisy image with a desired SNR. Finally, a pixel has finite dimensions while an edge is infinitely fine, so the location of an edge within a pixel could influence metrology errors. Our edge detection algorithm uses the $1 \times 5$ Sobel-like operator [-1 -2 0 2 1].

We simulate realistic SEM images where the true random rough edges are generated using the Thorsos method and the Palasantzas model with parameters specified in Ref. 2. We also simulate noisy SEM images for 14 straight edges each of which could have ten starting positions which are uniformly spread over three pixels; i.e., For each SNR level we are working with 140 flat lines to calculate $S_{noise}$ and 280 rough lines to estimate LER without the $S_{noise}$ correction. 2048 corrupted edge positions per line form the input to a multitaper spectrum estimator[10]. We approximate the true LER of rough lines from $S_{noise}$ and the power spectrum estimates of noisy rough lines. The flowchart in Figure 1 illustrates the procedure. Table 1 summarizes the performance of the estimates for the true value of LER at six choices of SNR and shows the greatest reduction of bias at low SNR, so this technique may be helpful for low-dose SEM images.

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2. T. Verduin, P. Kruit, and C. W. Hagen, SPIE J. Micro/Nanol., MEMS, MOEMS, **13**, 033009 (2014).
3. D. Li et al., J. Vac. Sci. Technol., B **34**, 06K604 (2016).
4. C. A. Mack, SPIE J. Micro/Nanol., MEMS, MOEMS, **12**, 033016 (2013).
5. L. Azarnouche, J. Applied Physics, **111**, 084318 (2012).

6. The authors thank Dr. J. S. Villarrubia for sharing the JMONSEL simulator with them.

7. R. L. Eubank, *Nonparametric Regression and Spline Smoothing* (CRC Press, New York, 1999), Second Edition.
8. B. D. Bunday and C. A. Mack, *Proc. SPIE* **9050**, 90500G (2014).
9. D. C. Joy, *Biological Low-Voltage Scanning Electron Microscopy*, edited by H. Schatten and J. Pawley (Springer, New York, 2008), pp. 129-144.
10. Y. Luo and S. A. Savari, "Multitaper and Multisegment Spectral Estimation of Line-Edge Roughness," to appear in *Proc. SPIE*, (2017).

| SNR | True LER | Estimated LER | | | |
|---|---|---|---|---|---|
| | | Without $S_{noise}$ correction | Accuracy | With $S_{noise}$ correction | Accuracy |
| $\sqrt{200}$ | 1.50nm | 1.499nm | -0.07% | 1.484nm | -1.07% |
| $\sqrt{100}$ | 1.50nm | 1.505nm | 0.33% | 1.484nm | -1.07% |
| $\sqrt{20}$ | 1.50nm | 2.988nm | 99.20% | 2.109nm | 40.60% |
| $\sqrt{10}$ | 1.50nm | 5.141nm | 242.73% | 2.790nm | 86.00% |
| $\sqrt{5}$ | 1.50nm | 6.531nm | 335.40% | 2.592nm | 72.80% |
| $\sqrt{2}$ | 1.50nm | 7.353nm | 390.20% | 1.736nm | 15.73% |

*Table 1:* LER estimate performance,
accuracy = (estimated LER - true LER) $\times$ 100% / true LER.
SNR = (average number of electrons per pixel)$^{0.5}$ in our Poisson noise model;
see Ref. 9 for SNR definition applying to secondary electron noise.

| SNR | $\sqrt{200}$ | $\sqrt{100}$ | $\sqrt{20}$ | $\sqrt{10}$ | $\sqrt{5}$ | $\sqrt{2}$ |
|---|---|---|---|---|---|---|
| $S_{noise}$ estimate | 0.045nm$^3$ | 0.063nm$^3$ | 4.475nm$^3$ | 18.627nm$^3$ | 35.919nm$^3$ | 51.029nm$^3$ |

*Table 2:* $S_{noise}$ estimate.

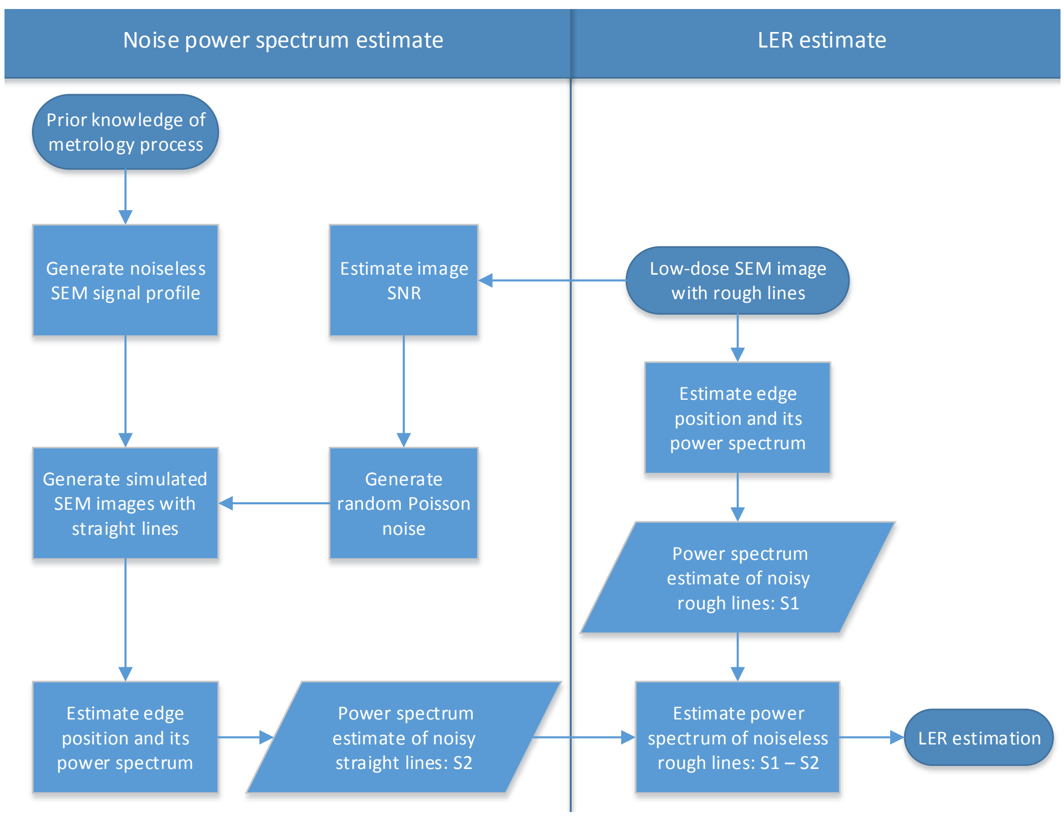


*Figure 1:* Flowchart of proposed method.