CD-SEM IMAGE DENOISING WITH UNSUPERVISED MACHINE LEARNING FOR BETTER DEFECT INSPECTION AND METROLOGY

Presentation · September 2020

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Bappaditya Dey, Sandip Halder, Kasem Khalil, Gian Lorusso, Joren Severi, Philippe Leray, Magdy A. Bayoumi, "SEM image denoising with unsupervised machine learning for better defect inspection and metrology," Proc. SPIE 11611, Metrology, Inspection, and Process Control for Semiconductor Manufacturing XXXV, 1161115 (22 February 2021); doi: 10.1117/12.2584803

Event: SPIE Advanced Lithography, 2021, Online Only

SEM image denoising with Unsupervised Machine Learning for better defect inspection and metrology

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ABSTRACT

CD-SEM images inherently contain a significant level of noise. This is because a limited number of frames are used for averaging, which is critical to ensure throughput and minimize resist shrinkage. This noise level of SEM images may lead to false defect detections and erroneous metrology. Therefore, reducing noise in SEM images is of utmost importance. Both conventional noise filtering techniques and recent most discriminative deep-learning based denoising algorithms are restricted with certain limitations. The first enables the risk of loss of information content and the later mostly requires clean ground-truth or synthetic images to train with. In this paper, we have proposed an U-Net architecture based unsupervised machine learning approach for denoising CD-SEM images without the requirement of any such ground-truth or synthetic images in true sense. Also, we have analysed and validated our result using MetroLER, v2.2.5.0. library. We have compared the power spectral density (PSD) of both the original noisy and denoised images. The high frequency component related to noise is clearly affected, as expected, while the low frequency component, related to the actual morphology of the feature, is unaltered. This indicate that the information content of the denoised images was not degraded by the proposed denoising approach in comparison to other existing approaches.

Keywords: CD-SEM, defect inspection, denoise, unsupervised, deep learning, line edge roughness, line width roughness, gaussian-mixture-model, Power Spectral Density (PSD), metrology.

1. INTRODUCTION

Scanning Electron Microscope (SEM) are used widely in the semiconductor industry for metrology and inspection. Among the various types of SEMs, CD-SEMs are of profound importance mainly because they measure the CD (critical dimension) of the circuit patterns based on which the entire litho process is targeted. Review-SEMs and E-beam inspection tools are gaining importance as we shrink to N3 nodes and below because of their high resolution. However, as circuit patterns become smaller (pitches less than 32 nm) the extraction of repeatable and accurate defect locations along with CD metrology becomes significantly complicated especially post ADI (After Develop inspection). This is simply because at these pitches the number of pixels available to detect a defect or do metrology is approaching single digit numbers. Hence, reducing noise in SEM images is of utmost importance.

The case of ADI SEM imaging is one of the most challenging tasks. Images are usually noisy when less number of frames are used. This often leads to false defect detections and erroneous metrology. Fig. 1 shows example of noisy SEM images for two different pitches. Detection of minute bridges and breaks and resist footing from these top down images is becoming more and more important. While there are various noise-removal techniques available today not all of them survive the requirements of the semiconductor industry at these advanced nodes. Also, the quantification of noise for SEM images does not fit truly Gaussian or Poisson distributions Ref. 1, as noise bias varies with metrology settings and sample properties. Recent discriminative deep learning-based algorithms have outperformed the conventional noise filtering methods. However, these methods need to be trained with clean ground-truth images which in most scenarios

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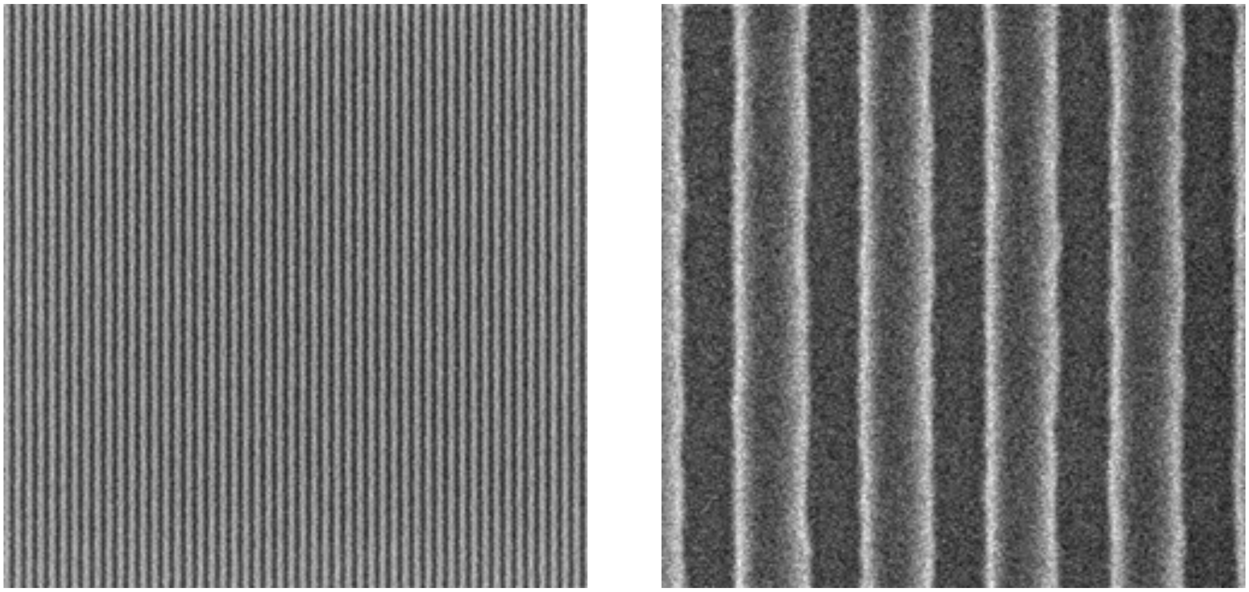
Metrology, Inspection, and Process Control for Semiconductor Manufacturing XXXV, edited by Ofer Adan, John C. Robinson, Proc. of SPIE Vol. 11611, 1161115
 · doi: 10.1117/12.2584803



(a) (b)
Figure 1: Noisy CD-SEM images (a) Pitch 32 and (b) Pitch 90.

do not exist. As an alternative, some methods have used synthetic noiseless images generated from software-tools for Supervised methods or have degraded the clean target with approximated noise level for Semi-Supervised methods. Often these methods require additional conditional files to generate the corresponding synthetic images and this may lead to an additive artefacts. Machine learning is significant in this issue. Currently, machine learning is significant for learning patterns for classification. Machine learning methods have been used in several domains such as speech recognition Ref. 2, hardware fault prediction Ref. 3, natural language processing Ref. 4, embryonic hardware system Ref. 5, image recognition Ref. 6. Machine learning is divided into supervised and unsupervised learning. In supervised learning, variables of input and output are given. The training is done using labeled data such as neural network Refs. 7–9, support vector machine Ref. 10, recurrent neural network Ref. 11, linear and logistics regression, etc. In unsupervised machine learning, variables of input only are given. The learning is done without labeled data such as K-means Ref. 12, Cluster algorithms Ref. 13, etc. We have applied an U-Net architecture based unsupervised machine learning approach for denoising SEM images without the requirement of any such ground-truth or synthetic image. This work addresses the following problems: (1) Denoising SEM images without clean target in true sense. The proposed method can be trained using only a single or few noisy SEM images. (2) Robustly detect the feature-edges from denoised images using unsupervised method for better metrology and defectivity inspection. The approach is tested for both simulated and real SEM images. Also, we have analysed and validated our result against conventional approach. Our unsupervised approach demonstrates its effectiveness both quantitatively and qualitatively.

The remainder of the paper is organized as follows. In section 2, we have introduced a brief overview of related works. In section 3, we have briefly discussed our proposed method and implementation details. In section 4, we have shown all experimental results and our analysis. In section 5, we have concluded the paper.

2. RELATED WORK

In this section, we briefly discuss some existing recent research approaches and methodologies in the context of SEM image denoising/quality enhancement techniques. Liangjiang Yu *et al.* Ref. 14 has proposed an unsupervised machine learning based SEM image quality enhancement framework as uMLIQE. This framework requires only noisy images. The authors captured noisy data pairs at random die locations without any frame averaging. The framework reportedly converges to a statistical mean of the desired target. The main drawbacks/limitations of this proposed method as reported are induced artifacts and contrast loss. In this paper, the authors have presented a deep learning-based method to realize accurate and stable CD measurement from SEM images with low SNR Ref. 15. They constructed the dataset used in deep learning training using a CD-SEM image model designed from mathematical and statistical line edge roughness (LER). This approach also has limitations due to induced artifacts. D. Cerbu *et al.* Ref. 16 has also presented similar work on SEM image denoising for a better metrology and defect inspection. The authors have trained a generative network with noisy images. The have used noiseless synthetic images and then added Gaussian white uncorrelated noise to it. For the discriminator network, they have used ideal/noiseless images. After training is completed, the generative network will act as a denoising filter. This is a nice approach to tackle noise in CD-SEM images but again limited with distortion/artifacts. N. Chaudhary *et al.* Ref. 17 proposed a deep supervised learning framework for the estimation of line edge roughness (LER) and line-width roughness (LWR) in low-dose scanning electron microscope (SEM) images. They have simulated a dataset of 100,800 SEM images constructed with the help of Thorsos method and the ARTIMAGEN library. Bappaditya Dey *et al.* Ref. 18 proposed an unsupervised deep learning-based approach to automatically detect the probable printable window. The proposed model enables to learn the characteristic features for a given dataset of numerous different CD-SEM images and then ranked them based on a numeric score-metric, derived from the comparison images in a N-dimensional latent feature space.

3. THE PROPOSED METHOD

The proposed denoising approach is based on Noise2Void training scheme introduced by Krull *et al.* Ref. 19. A noisy image x can be represented as:

$$x = s + n \tag{1}$$

Where s is the signal part and n is the noise. Any image denoising mechanism aims to separate the signal degrading noise from the noisy signal to generate clean signal as $[s = x - n]$ based on two assumptions: pixel values in s are not statistically independent and pixel values in n are conditionally independent given corresponding signal values.

In the context of noisy SEM images, we can summarize the above assumptions in mathematical form as:

- A joint probability distribution function p(s, n) to generate an image x as:

$$p(s, n) = p(s)p(n|s) \tag{2}$$

- Satisfying (a) as

$$p(s_i|s_j) \neq p(s_i) \tag{3}$$

  For 2 pixels i, j with a Receptive-Field (RF)

- Satisfying (b) as

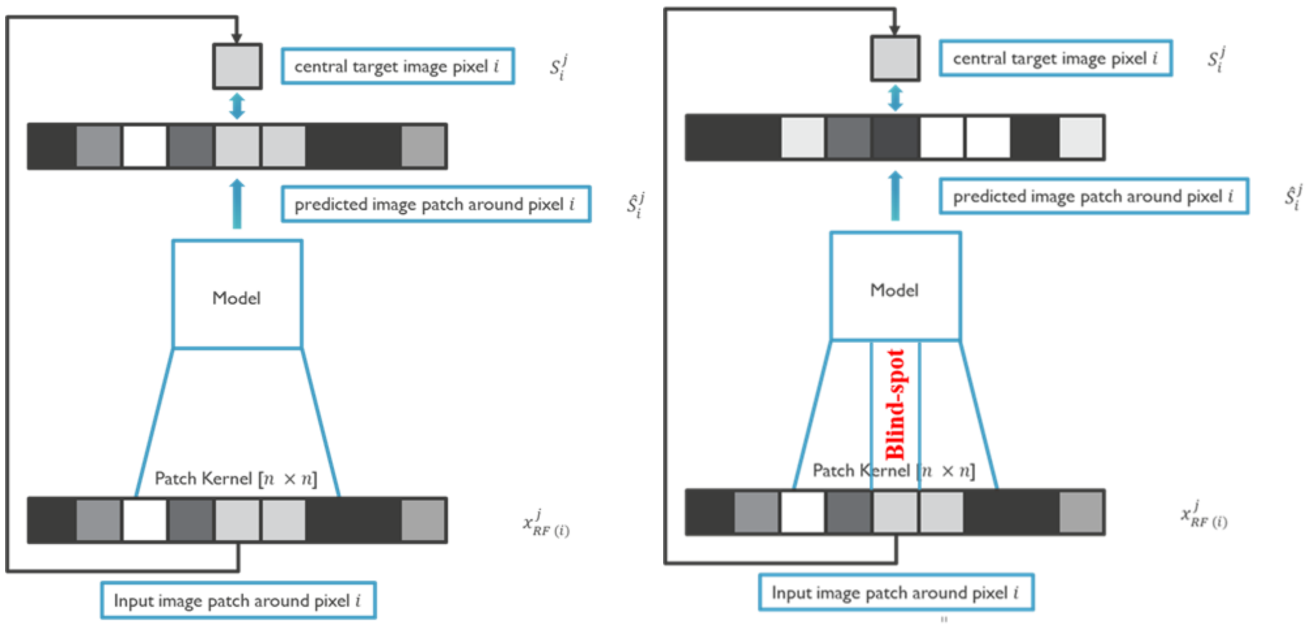
$$p(n|s) = \Pi_i p(n_i|s_i) \tag{4}$$

$$E[x_i] = s_i \rightarrow gt[noiselessimage] \; iff \; E[n_i] = 0 \tag{5}$$

We have applied an U-Net architecture based unsupervised machine learning approach for denoising SEM images without the requirement of any such ground-truth or synthetic image. We have used a single noisy SEM image both as an input and target during training of our algorithm. The conventional and the proposed framework based on Ref. 19 have been shown in Fig. 2. The loss function can be represented as:

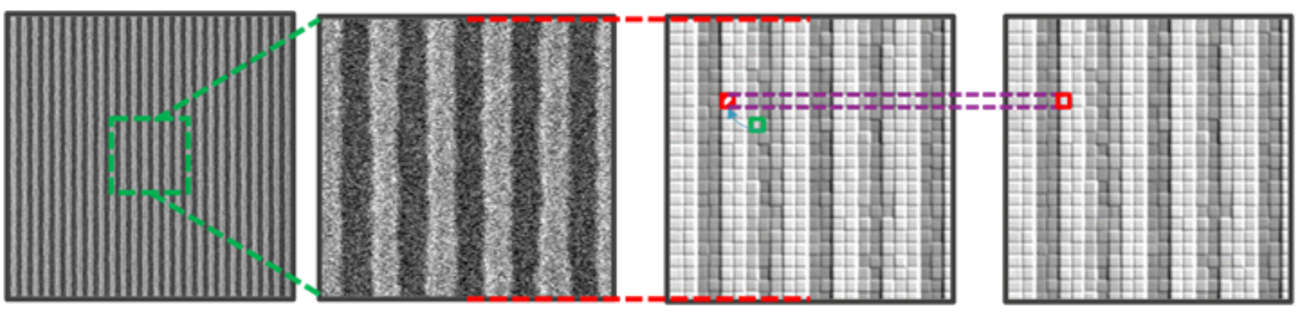
$$arg_w \; min \sum_j \sum_i \left(g(\tilde{x}^j_{RF(i)}; w), x^j_i\right) \tag{6}$$

Where $\tilde{x}^j_{RF(i)}$ is the receptive field of the model with blind-spot at the center as described in Fig. 3. Our goal is to minimize pixel-wise loss by fine tuning the parameters w. Due to the blind-spot mechanism the model is not able to learn the identity i.e. direct mapping from input patch to the target patch. Therefore, the model is able to estimate the signal part



(a) (b)

Figure 2: Conventional vs Proposed network.



(a) (b) (c) (d)

Figure 3: Blind-spot masking mechanism. (a) Original noisy SEM image. (b) image patch extracted from (a). (c) image is modified by replacing a target pixel (labelled red) with a randomly selected pixel value (labelled green) and thus creating a blind-spot. This modified image is used as input during model training. (d) target patch corresponding to (c) as original input patch without modification.

by analyzing the surroundings (statistical dependence) but carry no information about the noise part (statistically pixel-wise independent). Our model has been trained on Lambda TensorBook with NVIDIA RTX 2080 MAX-Q GPU. We have randomly extracted patches from a single noisy SEM image of size 64 ×64. We have set number of training iterations in the range of 100-150 based on model convergence performance with number of training steps per epoch as 200 to 400. We have set the size of training batches as 128, depth of U-Net as 2, size of convolution kernels in first layer as 3, initial learning rate as 0.0001, number of feature channels in the first U-Net layer as 32. The patches/dataset was divided into a training set and a validation set with percentage ratio of [60:40]. All the images are in TIFF format. The model was trained using Keras library Ref. 20 and the Tensorflow library Ref. 21 backend in the python programming environment. The Anaconda version was 4.6.8. Batch Normalization Ref. 22 is added to the U-Net Ref. 23 architecture before each activation function.

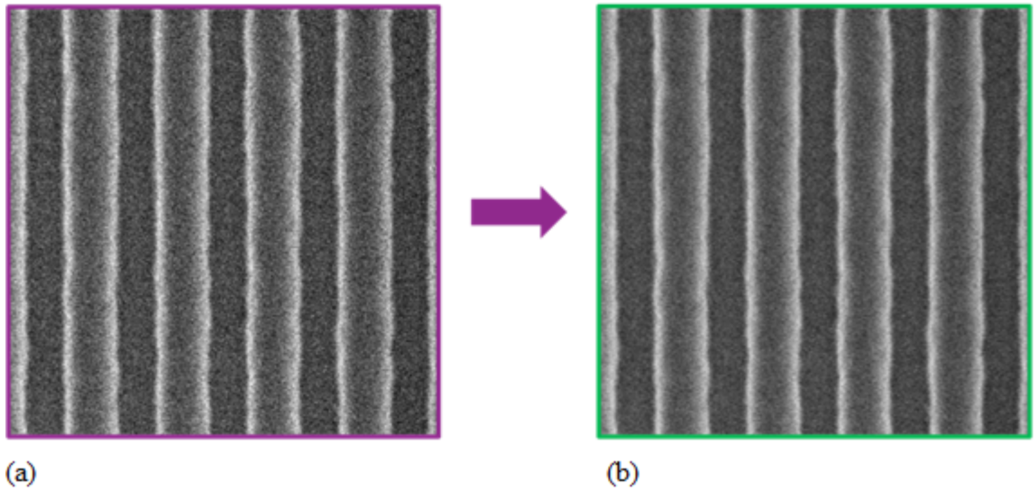


Figure 4: (a) Single noisy SEM image is given to the network model. (b) Denoised image generated by the network model without altering real signal.

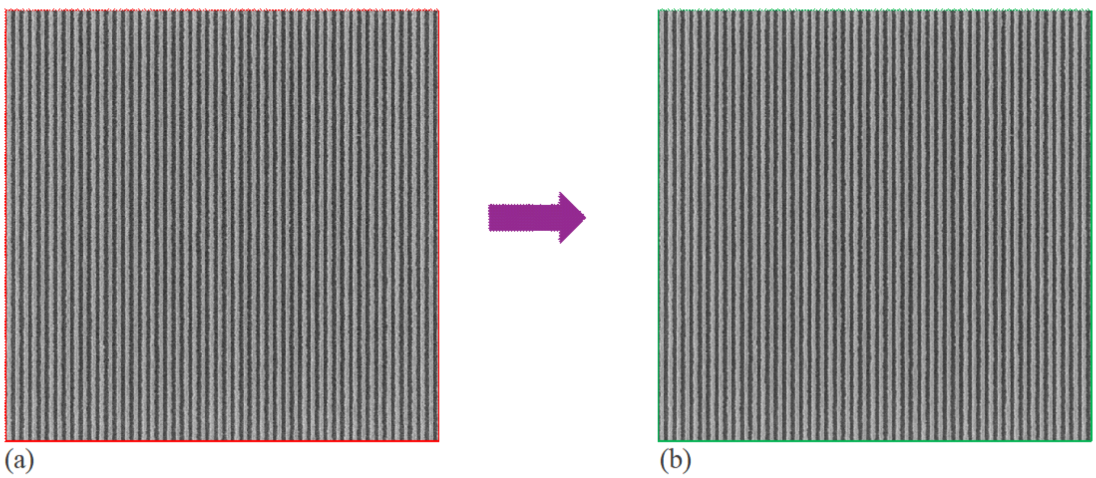


Figure 5: (a) Noisy SEM image P32 with Film thickness 30 nm (b) Denoised image.

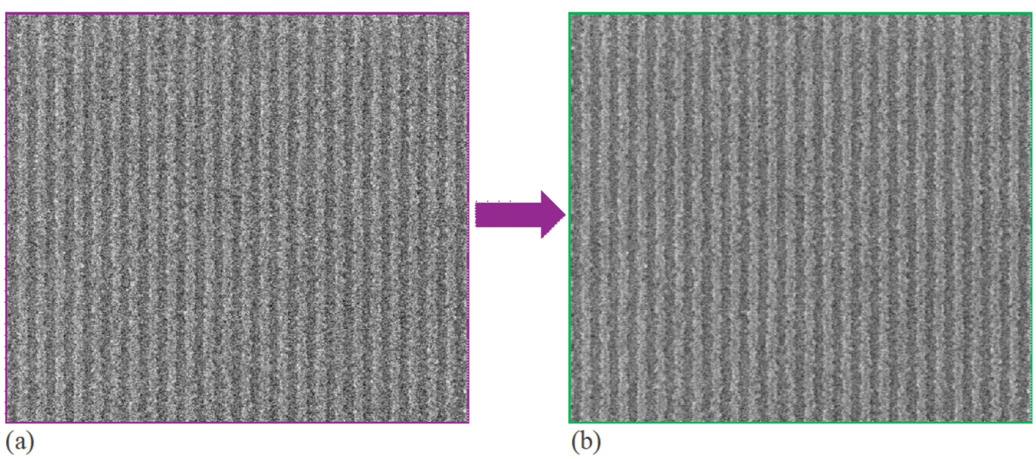
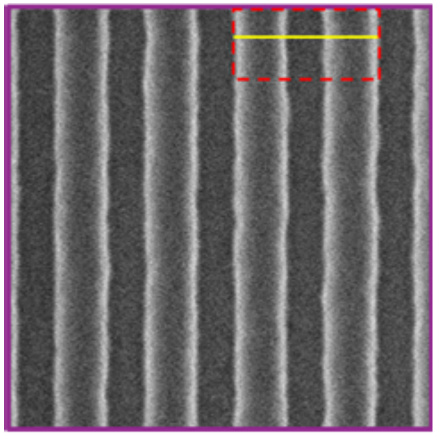
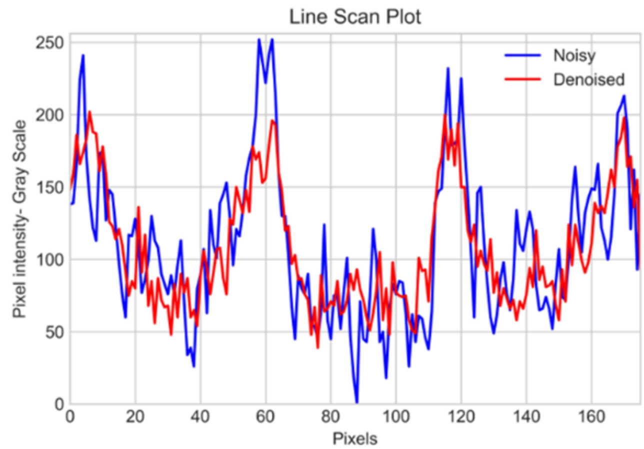


Figure 6: Cropped ROI for (a) Noisy SEM image P28 with Film thickness 8 nm [Thin Resist] (b) Denoised image.

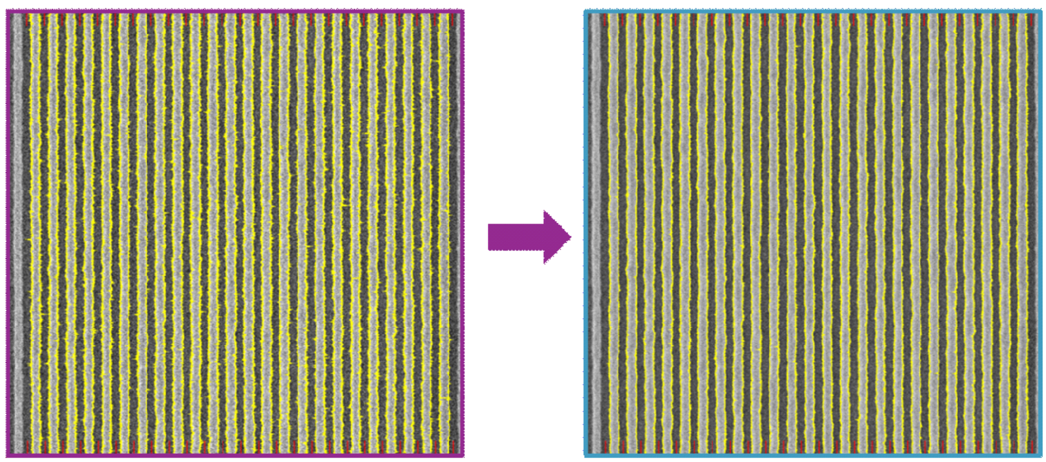


(a)



(b)

Figure 7: (a) Original noisy SEM image ROI [P90]. (b) Line Scan Plot comparison for both noisy and denoised SEM images ROI.



(a) (b)

Figure 8: SEM image analysis with Fractilia MetroLER library (a) Noisy image (b) Denoised images.

4. THE IMPLEMENTATION AND EXPERIMENTAL RESULT

Our proposed approach allows denoising of SEM images without requirement of any clean target (ideally noiseless) in true sense. In Fig. 4, Fig. 5 and Fig. 6, we have shown the results obtained from the proposed denoising approach for different pitches (as 90nm, 32nm, 28nm etc.) and with different film thicknesses (as 30 nm, 8 nm etc.). Fig. 7 shows the line-scan plots for both the noisy and denoised images. The two line-scans are overlapping one another, this indicates that the actual information content of the image was not degraded by the proposed denoising approach. Only noise part is removed as well as no contrast loss. We have analyzed each pair of original noisy image and its corresponding denoised image with Fractilia MetroLER v2.2.5.0. library Ref. 24. Fig. 8 shows detected edges for denoised image are with less spikes or almost without spikes in comparison to the original one. In Fig. 9, the power spectral density of a noisy and a denoised images are compared for Line-Width-Roughness (LWR). Power Spectral Density enables us to characterize the frequency behaviour of the roughness. The high frequency component related to noise is clearly affected, as expected, while the low frequency component, related to the actual morphology of the feature, is unaltered so that edge placement errors are not changing. This indicates that the information content of the images was not degraded by the proposed denoising approach. Fig. 10 depicts the Power Spectral Density (PSD) plot for Line-Edge-Roughness (LER). For biased part, the noise level

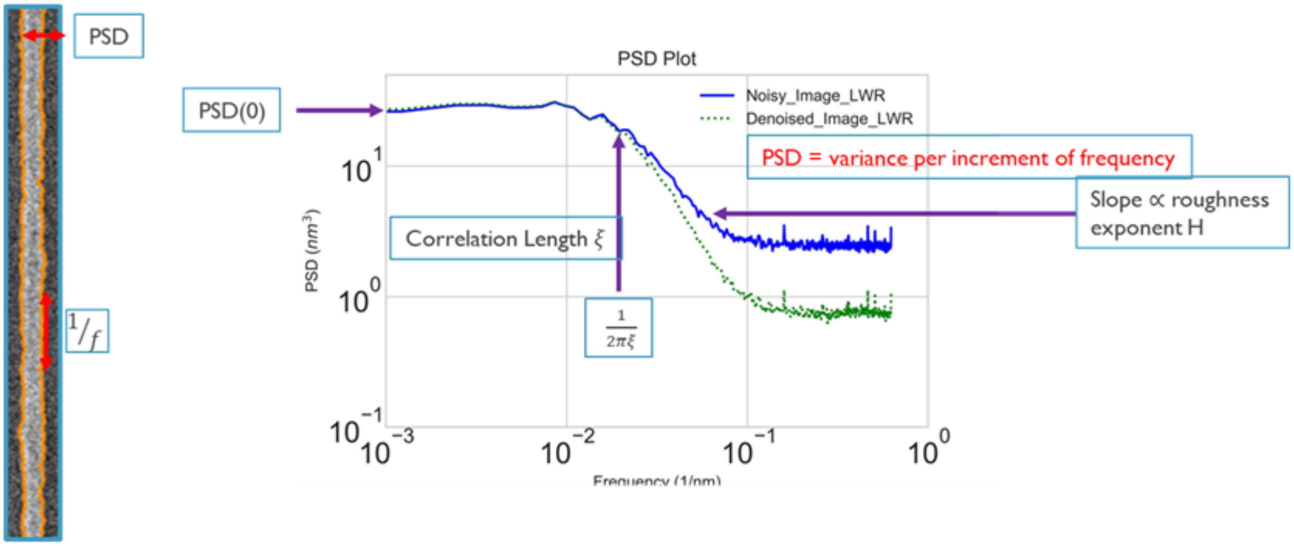
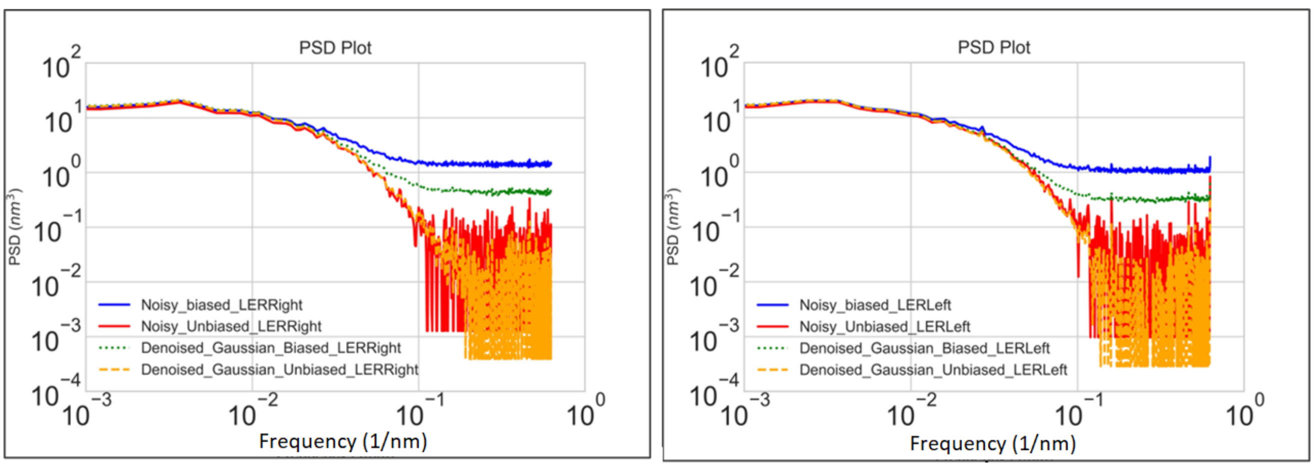


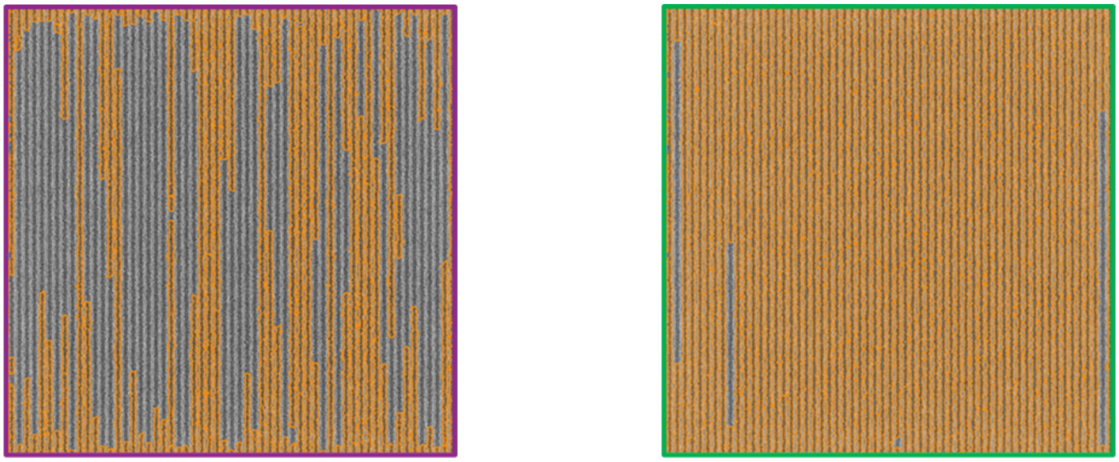
Figure 9: Power Spectral Density (PSD) plot for Line-Width-Roughness (LWR).



(a) (b)

Figure 10: Power spectral density (PSD) plot for Line-Edge-Roughness (LER).

is lowered significantly whereas the unbiased part is unaffected post denoising. We have applied the unsupervised GMM based segmentation method to extract the Critical Dimension (CD) or contour in noisy SEM images Refs. 25, 26. Fig. 11 shows, for noisy images we are missing the granularity for major pixels and thus cd extraction is failing whereas denoised image makes better CD extraction possible with same parameter settings for the algorithm in both scenarios. Therefore, this proposed deep learning based denoiser framework may be utilized as assist tool for defect inspection and better metrology. Our proposed approach also allows us to work with thin resists. Fig. 12 supports our claim that proposed denoiser as an assist tool for defect inspection. We have shown a comparative analysis for defect inspection for small bridge/gap and significance of stochastic noise on structure pixels for both noisy and denoised images. For noisy images, certainly more False Positive (FPs) defects are flagged due to the presence of stochastic noise on the body of SEM images. Therefore, leads to erroneous metrology which in turn leads to shape fidelity loss and finally yield loss. Whereas, for denoised images, we can correctly detect the defects (TPs) as stochastic noise has been removed or optimized.



(a) (b)

Figure 11: Unsupervised GMM based CD/Contour extraction: (a) noisy vs (b) denoised for Thin resist low-ft images.

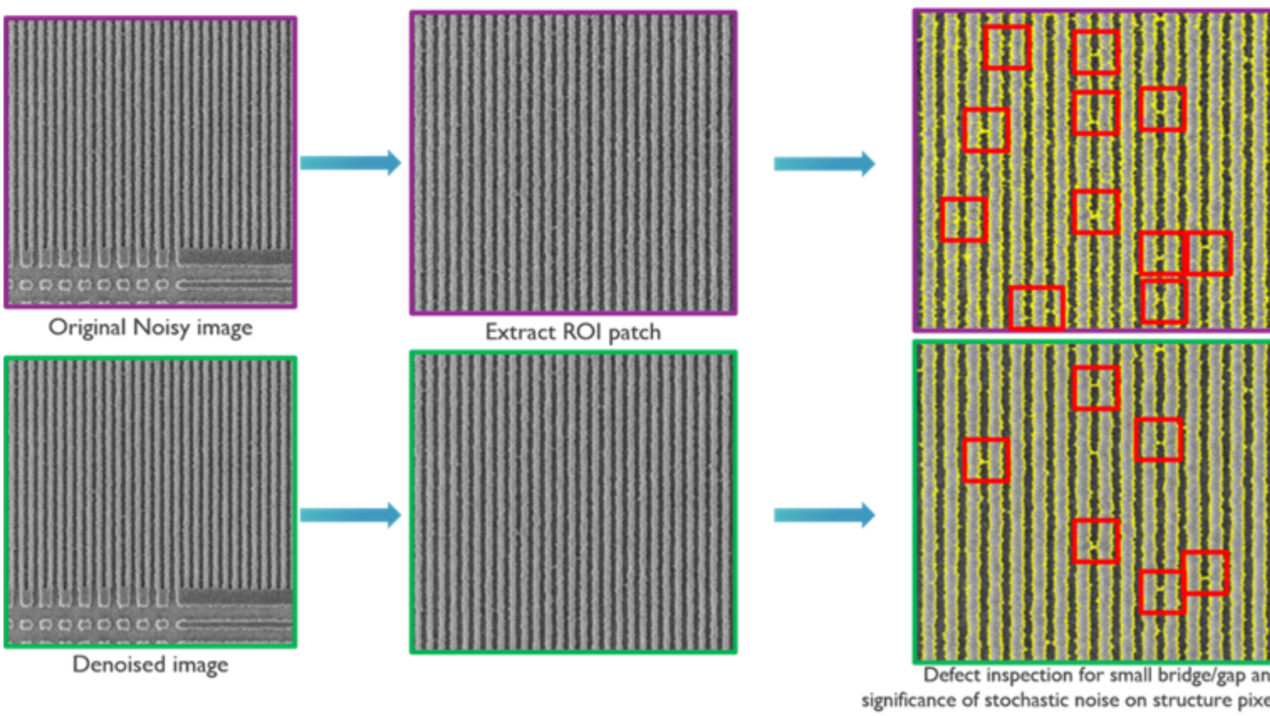


Figure 12: Defectivity analysis and accuracy metric comparison for Denoised image against Original noisy image.

5. CONCLUSION AND FUTURE WORK

The proposed method presented an unsupervised machine learning based SEM image denoising technique without the requirement of any ground-truth or synthetic images. The deep learning framework is based on a U-Net architecture. We have compared the power spectral density (PSD) of both a noisy and denoised image. The high frequency component related to noise is clearly affected, as expected, while the low frequency component, related to the actual morphology of the feature, is unaltered. This indicates that the information content of the denoised images was not degraded by our proposed denoising approach. We have also implemented unsupervised GMM based pattern classification and segregation technique to robustly detect feature edges from the denoised images. This approach helps to overcome the limitations of conventional edge-detection algorithms like Canny-edge detector in terms of parameter settings. This deep learning based denoiser framework may allow us to better identify defects as well as to work with thin resists. Our future goal is to improve the model accuracy and performance by using an arbitrary noise model obtained from a set of SEM images subject to uniform noise type.

6. ACKNOWLEDGEMENTS

The authors used the imec Leuven research computing facility to conduct part of the research. We thank Danilo De Simone, Mihir Gupta, Victor Blanco and Sayantan Das for their assistance in data preparation. We thank Mircea Dusa, Dorin Cerbu and other colleagues who provided insight and expertise that helped us to improve the manuscript.

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