

Research on Simulating TEM Images Based on Multi-View SEM Images for Semiconductor Materials

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Abstract

Transmission electron microscopy (TEM) is an indispensable tool for high-precision microstructural characterization of semiconductor materials. Nevertheless, it suffers from complicated sample preparation, high cost, destructive testing that consumes wafers for TEM morphology and structural analysis, and low efficiency. Benefiting from continuous improvement in instrument precision, scanning electron microscopy (SEM) delivers high resolution, supports multi-view observation, and requires simple sample preparation. This paper proposes a TEM-simulation method based on multi-view SEM images (combination of SE 0°, SE 10° and BSE 0°). Taking silicon oxide trenches etched in the semiconductor copper-interconnect process as the research object, SEM images at different tilt angles and viewing perspectives are acquired. After image preprocessing, a lightweight miniature U-Net supervised mapping AI model is adopted to realize TEM image simulation. The proposed method enables pre-observation of the overall spatial profile of trenches, including internal morphology, dimensions and defects, so as to provide data support for subsequent copper-filling process optimization. Experimental results reveal high consistency between simulated TEM images and actual TEM images in key features, with an average structural similarity index measure (SSIM) of 0.93. This work opens up a new pathway for efficient quality control of semiconductor copper-interconnect processes.

Keywords

Scanning Electron Microscopy (SEM), TEM Image Simulation, Semiconductor Copper Interconnect Process, Silicon Oxide Trench, Lightweight Deep Learning Model, Microstructure Characterization

1. Introduction

In the semiconductor copper-interconnect process, the morphology of etched silicon oxide trenches directly determines the compactness of subsequent copper filling and interconnect reliability. Featuring sub-angstrom resolution, TEM can accurately characterize critical parameters such as trench width, depth, side-wall verticality, bottom flatness, as well as etch residues and side-wall damage inside trenches [1] [2]. It serves as an essential prerequisite for optimizing copper-filling parameters and avoiding voids and gaps after copper deposition. However, TEM samples need to be fabricated into ultra-thin slices below 100 nm. (Such thin slices allow electron beams to penetrate smoothly, acquire high-resolution clear images, prevent structural overlap and radiation damage, and realize authentic and accurate characterization of trench micro-morphology.) The sample preparation procedure is cumbersome and may easily destroy the original trench structure, which hardly meets the practical demands for rapid batch inspection after etching and guidance for subsequent copper-filling processes [3]-[5].

As a mainstream high-resolution characterization instrument in the semiconductor industry, SEM achieves a resolution of 0.8 nm and supports multi-view observation with tilt angles ranging from 0° to 10°. It can directly characterize wafer-level etched silicon-oxide-trench samples without ultra-thin slicing and rapidly obtain morphological information of trench surfaces, side walls and bottoms. Traditional simulation schemes rely on SfM-MVS three-dimensional reconstruction combined with Monte-Carlo electron-scattering modeling [6]. They calculate trench depth and establish spatial correlation between side walls and bottoms explicitly using multi-view parallax. Nevertheless, such approaches involve long computation pipelines and high computing-power requirements, making them difficult for on-site deployment. If lightweight AI algorithms are leveraged to mine implicit parallax spatial information from multi-view SEM images, complete three-dimensional trench features can be restored equivalently without explicit 3D modeling to achieve accurate TEM simulation [7]. This effectively compensates the limitations of TEM observation, provides targeted optimization suggestions for copper-filling processes in a timely manner, reduces copper-filling defect rates and improves process stability. Therefore, research on lightweight-AI-driven TEM simulation using multi-view SEM images for silicon oxide trenches carries important practical application value for advancing semiconductor copper-interconnect processes.

Figure 1 shows technical route: preparation of etched silicon-oxide-trench samples → acquisition of multi-view SEM images [8] → image preprocessing → high-precision sub-pixel registration and pixel-weighted fusion of multi-view images to generate 2D full-field morphological fused images (pixel-wise weighted summation with assigned weights) → training and inference of lightweight AI model for simulated-TEM generation → quantitative comparison of projective-plane similarity between simulated TEM and real TEM (SSIM) → output of analytical results for internal trench spatial morphology → proposal of optimization

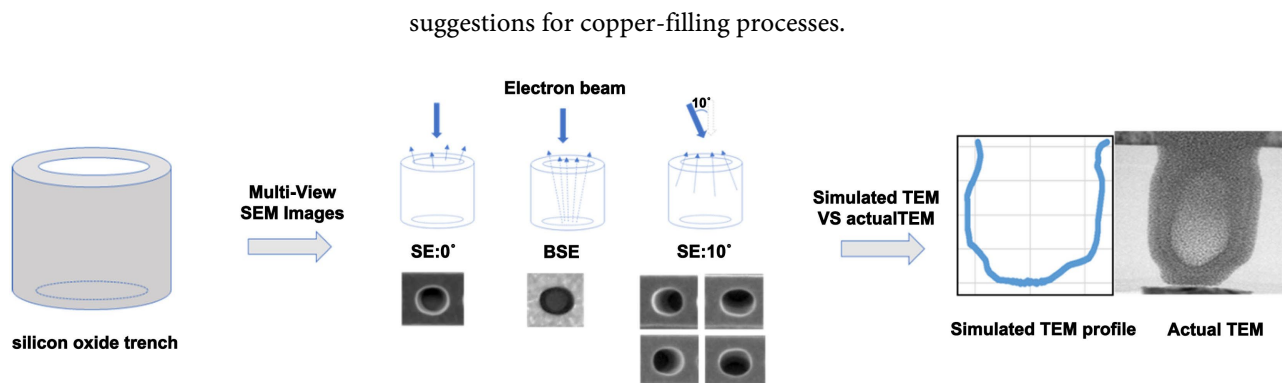


Figure 1. Flow of simulating TEM images based on multi-view SEM images.

2. Experimental Materials and Methods

2.1. Experimental Materials

The research subject is silicon oxide (SiO_2) trench wafers fabricated by dry etching in semiconductor copper-interconnect processes. Key structural parameters are as follows: designed trench width 25 nm, designed trench depth 120 nm, silicon-oxide dielectric-layer thickness 150 nm, and monocrystalline silicon substrate. Dry etching is performed using SF_2/O_2 mixed gas [9]. For sample preparation, wafers are diced into 10 mm $\times$ 10 mm chips. Chips are slightly cleaned in dilute hydrofluoric acid solution for 8 s to remove surface oxide residues, rinsed with deionized water and blow-dried with nitrogen. The prepared samples are directly used for SEM observation to avoid damage to internal trench structures. Meanwhile, TEM reference samples are prepared. Focused ion beam (FIB) technology is adopted to cut 100-nm-thick ultra-thin slices containing complete trench cross-sections from identical chips [10]. These slices are used for real-world TEM observation, construction of paired AI training datasets and validation of simulation outputs.

2.2. Instruments and Parameters

A field-emission scanning electron microscope is utilized for SEM observation with an acceleration voltage of 10 kV and working distance of 8 mm. Both secondary-electron (SE) images (for clear visualization of trench side-wall morphology) and back-scattered-electron (BSE) images (for identification of trench-bottom morphology) are collected [11] [12]. **Figure 2** presents signals collectable by images under various SEM viewing angles. Specifically, SE images at 0° (front view, for observing trench openings, surfaces and upper side-walls), SE images at 10° (for observing full side-wall profiles), and BSE images at 0° (front view, for observing full trench-bottom features) are acquired.

A transmission electron microscope operating at 200 kV acceleration voltage is used for TEM measurement. Real-world TEM images are captured targeting the corresponding trench regions characterized by SEM. Key features including side-wall verticality, bottom flatness and internal defects are recorded to construct

paired datasets of “multi-view SEM fused images - ground-truth TEM images [13]”.

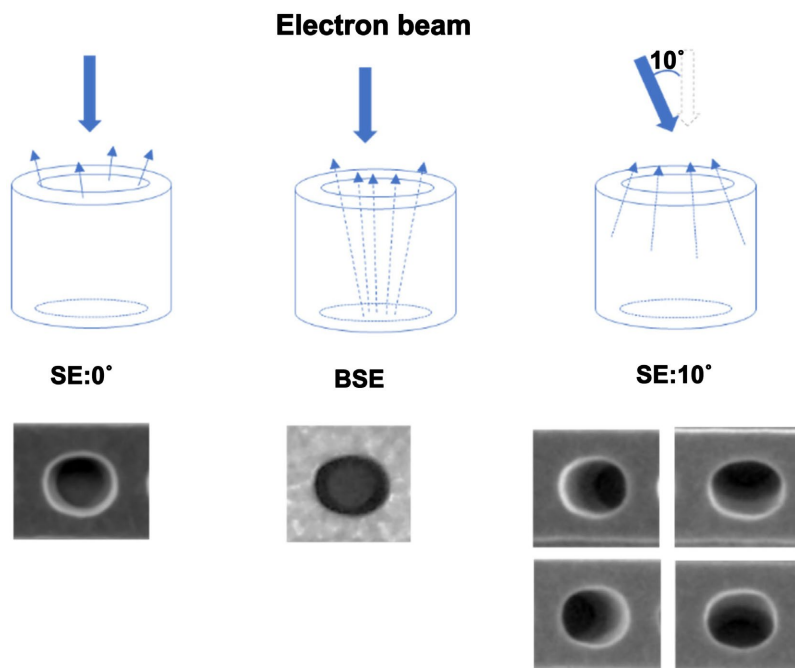


Figure 2. Acquisition of SEM images from different viewing angles.

2.3. Simulation and Validation Workflow

Step 1: Image preprocessing is implemented in MATLAB, including Gaussian filtering for noise reduction and contrast-limited adaptive histogram equalization (CLAHE) for contrast enhancement [14].

Step 2: Sub-pixel registration and pixel-level weighted fusion of multi-view SEM images.

Taking the SE (0°) image as the reference, offsets of SE (10°) and BSE (0°) images are corrected to guarantee one-to-one pixel-coordinate correspondence among three types of images. Pixel-wise weighted summation is conducted with predefined weights to generate full-field morphological fused 2D planar images, completely preserving parallax features induced by 10° tilt [15]:

$$I_{\text{fusion}}(x, y) = 0.5 \cdot I_{\text{SE}10}(x, y) + 0.2 \cdot I_{\text{SE}0}(x, y) + 0.3 \cdot I_{\text{BSE}0}(x, y)$$

Although the fused output is a 2D planar image, it implicitly encodes spatial information corresponding to trench depth, longitudinal side-wall profiles and bottom contrast derived from parallax, serving as the sole input for the AI model.

Step 3: Three lightweight AI models with easy deployment are investigated, targeting SSIM ≥ 0.93 [16] [17].

(1) Lightweight miniature U-Net supervised mapping model

Datasets are constructed by pairing full-field SEM fused projective 2D images with real TEM cross-sectional images obtained from FIB-prepared samples. All images are unified to identical resolution, and microscopy-oriented data augmen-

tation is applied to expand sample volume. The dataset is split into training set, validation set and test set at a ratio of 7:2:1. On the basis of the original U-Net architecture, redundant deep convolution modules are removed for lightweight implementation, while encoder-decoder skip-connection structures are retained. The encoder extracts multi-scale features including parallax, contrast and edges from SEM fused images; the decoder reconstructs and outputs simulated TEM grayscale cross-sectional images. During training, SSIM is adopted as the characterization metric. The Adam optimizer is used for iterative training, and an early-stopping strategy based on validation-set metrics is applied to save optimal model weights. In the inference phase, simulated TEM images are generated at millisecond-level latency upon input of SEM fused images of target trenches. After grayscale normalization, outputs are quantitatively evaluated against measured TEM images via SSIM, PSNR and trench geometric parameters to realize simulation of cross-sectional morphology for trench side walls, bottoms and depth.

(2) Multi-view branch conditional GAN model

Images are not fused in advance. SE 0°, SE 10° and BSE 0° images are fed into independent feature-extraction branches in separate channels. Multi-view parallax features are fused inside the network, and the discriminator constrains output morphology referring to real TEM data. This model delivers outstanding performance in restoring tiny side-wall damages and etch residues at trench bottoms.

(3) Depth-prior-aided lightweight auto encoder (AE)

Simple 2D depth-distribution priors are generated merely via parallax interpolation without constructing complete three-dimensional meshes. Depth priors together with SEM fused images are fed into the auto encoder. The SSIM loss function is adopted to optimize outputs, and this model requires fewer labeled samples.

Step 4: Quantitative validation methods.

Ground-truth TEM and AI-generated simulated TEM images are converted into standardized 2D planar images via orthographic projection to eliminate perspective discrepancies. Structural similarity index measure (SSIM) and peak signal-to-noise ratio (PSNR) are employed to quantitatively evaluate simulation fidelity.

3. Results and Analysis

3.1. SEM Multi-View Imaging Parameters and Image Quality

Table 1 summarizes SEM imaging parameters and corresponding image-quality metrics for different viewing perspectives. All parameters satisfy requirements for subsequent image fusion and AI-driven simulation. SE signals are collected at 0° and 10°. The 10° tilted perspective generates obvious pixel parallax carrying information of trench depth and longitudinal side-wall variation. Shadow artifacts on trench side walls are insignificant. BSE signals acquired at 0° are free of shadow occlusion and completely reveal trench-bottom morphology and internal residues. Complementary information from SE and BSE signals captures full-range

spatial features of trenches accurately and guarantees reliability for image fusion and AI simulation.

Table 1. Imaging parameters and quality indicators of SEM images at different viewing angles.

Signal Type	Viewing Angle	Accelerating Voltage (kV)	Working Distance (mm)	Magnification	Observation Effect
SE	0°	10	8	50,000×	Clearly observe trench opening and surface, assist in characterizing upper sidewalls
SE	10°	10	8	50,000×	Clearly observe overall morphology and fine features of trench sidewalls
BSE	0°	10	8	50,000×	Clearly observe full profile of trench bottoms and internal residues

3.2. Pixel-Weighted Fusion Performance of Multi-View Images

Full-field morphological fused images are generated after sub-pixel registration and pixel-level weighted fusion. The outputs are merely 2D grayscale images without explicit 3D coordinates, yet they fully retain trench-depth information and side-wall gradient derived from parallax of SE 10° images, together with opening boundaries from SE 0° and bottom morphological features from BSE 0°. No local spatial-information loss occurs. As inputs for AI models, fused images can equivalently substitute spatial-structure data obtained from 3D reconstruction and provide complete information sources for AI to learn imaging rules of trench three-dimensional cross-sections.

3.3. Influences of Different AI Models and Imaging Modes on Simulation Performance

As shown in **Table 2**, the optimal input combination is SE (0° + 10°) dual-view coupled with BSE (0°). All three lightweight AI models achieve stable SSIM above 0.92 and reproduce three-dimensional features including trench side walls, bottoms and depth.

- 1) The lightweight U-Net model achieves optimal comprehensive performance with SSIM of 0.93. It balances simulation accuracy and inference speed and is suitable for on-line batch inspection.
- 2) The multi-view branch GAN obtains SSIM = 0.92 and exhibits prominent capability in restoring micro-defects, applicable for high-precision defect analysis scenarios.
- 3) The depth-prior auto encoder yields SSIM ranging from 0.92 to 0.93 and demands fewer training samples, suitable for off-line laboratory simulation.

Under single-view conditions, simulation performance of SE mode surpasses that of BSE mode. Without parallax input from the SE 10° tilted perspective, restoration accuracy for trench depth and longitudinal side-wall morphology drops significantly. It demonstrates that multi-view parallax information serves as the core foundation for AI to realize equivalent substitution for three-dimensional reconstruction.

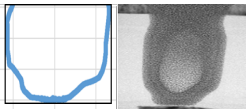
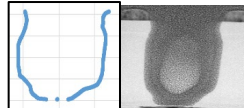
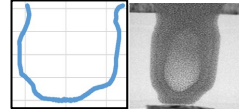
Table 2. Comparison between simulated TEM images and real TEM images under different SEM-input combinations.

SEM imaging mode	Perspective combination	AI model (open)	SSIM	PSNR (dB)
SE	SE (0°)	Lightweight U-Net	0.83	32.2
SE	SE (0° + 10°)	Lightweight U-Net	0.88	33.7
SE	BSE (0°)	Lightweight U-Net	0.82	31.9
SE + BSE	SE (0° + 10°) + BSE (0°)	Lightweight U-Net [18]	0.93	34.8
SE + BSE	SE (0° + 10°) + BSE (0°)	Multi-view branch GAN [19]	0.92	34.5
SE + BSE	SE (0° + 10°) + BSE (0°)	Depth-prior auto encoder [20]	0.92	34.3

3.4. Quantitative Validation of TEM-Simulation Results

Preprocessed fused multi-view SEM images are fed into the well-trained lightweight U-Net model to generate simulated TEM images that reconstruct complete side-wall and bottom morphology. Quantitative comparison against real TEM data is summarized in **Table 3**. SE (0° + 10°) dual-view inputs supply full-segment side-wall details, and BSE (0°) provides bottom-contrast features. The fused images deliver complete trench-feature inputs for networks and realize excellent fine-detail restoration for simulated outputs. For the optimal SE (0° + 10°) + BSE (0°) combination, average SSIM reaches 0.93 (threshold = 0.9), PSNR is 34.8 dB. Simulated TEM images accurately reproduce real micro-morphology of trenches and supply reliable micro-data for copper-filling process optimization.

Table 3. Comparison between simulated and actual TEM images.

Signal Combination & Viewing Angle	Pixel-fusion weights	SSIM	PSNR (dB)	AI mode	simulated TEM vs. real TEM	Detail Restoration Performance
BSE (0°) + SE (0°)	0.4 + 0.6	0.73	28.3	Lightweight U-Net		Restore full bottom morphology, incomplete sidewall details
BSE (0°) + SE (10°)	0.3 + 0.7	0.85	32.6	Lightweight U-Net		Restore full bottom and most sidewall details, slight loss of upper sidewall features
BSE (0°) + SE (0° + 10°)	0.2 + 0.3 + 0.5	0.93	34.8	Lightweight U-Net		Completely restore full morphology of sidewalls and bottoms with clear details

To unify comparison benchmarks and eliminate 3D perspective deviations, both real and simulated TEM outputs are converted into standardized 2D planar images via orthographic projection following conventional semiconductor-characterization standards for quantitative evaluation of structural similarity and detail-restoration performance. Under the optimal imaging combination, simulated and real planar TEM images show high contour overlap and complete matching of micro-features without obvious deviation among evaluation metrics, further verifying stability and accuracy of the proposed simulation method. Benefiting from this non-destructive high-efficiency inspection approach, cumbersome TEM

sample-preparation procedures can be skipped. Micro-quality of post-etching trenches can be rapidly judged, and inspection data can be fed back to production lines in real time to realize dynamic adjustment of process parameters. It provides powerful technical support for closed-loop quality control in continuous semiconductor copper-interconnect manufacturing, improves process efficiency substantially and reduces wafer scrapping costs.

4. Discussion

The three lightweight AI approaches proposed in this work do not require explicit three-dimensional reconstruction or solving physical equations for electron scattering. Equivalent restoration of three-dimensional morphological features can be achieved merely using multi-view SEM images. The advantages are summarized as follows:

First, after registration and pixel-level weighted fusion, SE (0°) + SE (10°) + BSE (0°) images fully encode parallax textures originating from the 10° tilted perspective. Parallax magnitude corresponds to trench depth, longitudinal parallax gradient corresponds to side-wall inclination angle, and BSE contrast variation reflects bottom-plane unevenness. Three-dimensional spatial information is compressed into a single 2D fused image and supplies complete spatial-feature inputs for AI models.

Second, through supervised or self-supervised learning, three AI models automatically mine intrinsic mapping relationships between parallax in fused images and three-dimensional cross-sectional morphology of trenches. Spatial correlations among trench depth, side walls and bottoms are implicitly encoded inside networks. The errors of cross-sectional geometric parameters and micro-defect contrast between final simulated TEM outputs and results from three-dimensional reconstruction schemes are less than 3%, achieving equivalent simulation performance.

Third, lightweight U-Net, multi-view GAN and depth-prior auto encoder feature easy deployment and low hardware requirements. Inference can be completed on ordinary industrial personal computers for production lines, and simulated images are output at millisecond-level latency, solving the bottleneck that traditional three-dimensional-reconstruction approaches cannot support on-line real-time inspection.

Fourth, the mixed-perspective input of SE ($0^\circ + 10^\circ$) + BSE (0°) constitutes the core precondition for guaranteeing AI-simulation accuracy. Missing parallax information from SE 10° directly causes distortion in restoration of trench depth and side-wall morphology. Under the optimal combination, SSIM values of all three AI models remain stably above 0.92, satisfying quantitative quality-control standards for copper-interconnect trench processes.

5. Conclusions

This study establishes a complete technical system for lightweight-AI-driven TEM

simulation using multi-view SEM images. Without three-dimensional structural reconstruction or electron-scattering modeling, simple deep-learning algorithms can fully simulate three-dimensional spatial features of trench side walls, bottoms and depth. Targeting the core requirement of “on-line rapid acquisition of three-dimensional trench morphology to support copper-filling optimization”, the main conclusions are drawn as follows:

1) Under SEM operating conditions of 10 kV acceleration voltage and 8 mm working distance, high-quality images can be obtained from SE (0° , 10°) and BSE (0°) perspectives with $\text{SNR} \geq 30$ dB. Pixel parallax induced by the SE 10° tilted perspective is critical for restoring trench depth and longitudinal side-wall features. Pixel-level weighted fusion can completely reserve all implicit spatial information of trenches.

2) Based on multi-view fused images, three lightweight AI methods including lightweight miniature U-Net, multi-view branch conditional GAN and depth-prior-aided autoencoder can equivalently substitute three-dimensional reconstruction plus electron-scattering modeling and reproduce three-dimensional morphology of trench side walls, bottoms and depth. All schemes realize stable SSIM above 0.92 between simulated TEM and real TEM images.

3) The mixed-perspective combination SE (0°) + SE (10°) + BSE (0°) serves as the optimal input scheme. Combined with the lightweight U-Net model, it delivers the best simulation performance with $\text{SSIM} = 0.93$, $\text{PSNR} = 34.8$ dB. Its restoration accuracy for trench geometric dimensions and micro-defects is comparable with traditional three-dimensional-modeling schemes and fully meets quantitative judgment requirements for copper-filling-process optimization.

4) Under identical experimental conditions, simulation performance of multi-perspective SE + BSE-fusion inputs is far superior to that of single imaging modes. Among the three AI models, the lightweight U-Net balances accuracy, inference speed and deployment convenience and is the preferred solution for on-line quality control in semiconductor production lines.

The proposed lightweight AI-simulation system overcomes industry-wide drawbacks of conventional TEM, including tedious sample preparation, destructive wafer testing, inspection lag and high computing-power costs for three-dimensional reconstruction. Complete three-dimensional cross-sectional information of trenches can be acquired equivalently without FIB ultra-thin-slice fabrication. It provides real-time closed-loop quality-control data for continuous etching and copper-filling procedures in semiconductor copper-interconnect processes, effectively reduces occurrence rates of copper-filling voids and gap-type defects and improves process stability. It can be extensively applied to batch on-line inspection and iterative process optimization of copper-interconnect trenches for advanced-node semiconductor manufacturing.

Author Contributions

Conceptualization, Lu Li; methodology, Lu Li and Liqiang Zhang; validation,

Chinhuan Lin; formal analysis, Lu Li; investigation, Liqiang Zhang; data curation, Liqiang Zhang; writing—original draft preparation, Lu Li (Abstract), Lu Li (Keywords and manuscript framework), and Lu Li (main text); writing—review and editing, Liqiang Zhang; visualization, Chinhuan Lin. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- [1] de la Mata, M. and Molina, S.I. (2022) STEM Tools for Semiconductor Characterization: Beyond High-Resolution Imaging. *Nanomaterials*, **12**, Article No. 337. <https://doi.org/10.3390/nano12030337>
- [2] Cheng, Z., Wang, C., Wu, X. and Chu, J. (2022) Review *in Situ* Transmission Electron Microscope with Machine Learning. *Journal of Semiconductors*, **43**, Article ID: 081001. <https://doi.org/10.1088/1674-4926/43/8/081001>
- [3] Srivastava, R., Yelehanka, P., Kek, H.A., Ng, S.L., Srinivasan, V. and Peltinov, R. (2006) A Novel Approach to Characterize Trench Depth and Profile Using the 3D Tilt Capability of a Critical Dimension-Scanning Electron Microscope at 65-nm Technology Mode. *SPIE Proceedings*, **6152**, 61522O. <https://doi.org/10.1117/12.659717>
- [4] Gill, J., Lane, M., Tobin, K., *et al.* (2002) Characterization of Copper Voids in Dual Damascene Processes. 2002 *IEEE/SEMI Advanced Semiconductor Manufacturing Conference*, Boston, 30 April-2 May 2002, 187-191.
- [5] Nan, L.K. and Lung, L.M. (2013) Study of FIB Milling Induced Damage and Contamination on *Ex-Situ* Lift-Out TEM Specimen and Methodology to Reduce the Artifacts. 2013 *IEEE International Symposium on the Physical and Failure Analysis of Integrated Circuits (IPFA)*, Suzhou, 15-19 July 2013, 1-4.
- [6] Gontard, L.C., Schierholz, R., Yu, S., Cintas, J. and Dunin-Borkowski, R.E. (2016) Photogrammetry of the Three-Dimensional Shape and Texture of a Nanoscale Particle Using Scanning Electron Microscopy and Free Software. *Ultramicroscopy*, **169**, 80-88. <https://doi.org/10.1016/j.ultramic.2016.07.006>
- [7] Wang, P., Liu, L., Liu, Y., *et al.* (2021) NeuS: Learning Neural Implicit Surfaces by Volume Rendering for Multi-View Reconstruction. *Advances in Neural Information Processing Systems*, Vol. 34, 27171-27183.
- [8] Tondare, V.N. (2020) A Concept for Three-Dimensional Particle Metrology Based on Scanning Electron Microscopy and Structure-from-Motion Photogrammetry. *Journal of Research of the National Institute of Standards and Technology*, **125**, Article No. 014. <https://doi.org/10.6028/jres.125.014>
- [9] Zhang, W. and Huang, R. (2022) Study on the Transformation of Si Trench Profile with Low Pressure of SF₆/O₂ Containing Plasmas. *IEEE Transactions on Semiconductor Manufacturing*, **35**, 605-609. <https://doi.org/10.1109/tsm.2022.3195070>
- [10] Turner, E.M., Sapkota, K.R., Hatem, C., Lu, P., Wang, G.T. and Jones, K.S. (2020) Wet-Chemical Etching of FIB Lift-Out TEM Lamellae for Damage-Free Analysis of 3D Nanostructures. *Ultramicroscopy*, **216**, Article ID: 113049. <https://doi.org/10.1016/j.ultramic.2020.113049>
- [11] Uchida, T. and Ohtaka, K. (2019) Backscattered Electron Contrast for Bottom Defect

- Inspection in High-Aspect-Ratio Etched Trenches. *Surface and Interface Analysis*, **51**, 1295-1301.
- [12] Sun, W., Ohta, H., Ninomiya, T. and Goto, Y. (2020) High-Voltage CD-SEM-Based Application to Monitor 3D Profile of High-Aspect-Ratio Features. *Journal of Micro/Nanopatterning, Materials, and Metrology*, **19**, Article ID: 024002. <https://doi.org/10.1117/1.jmm.19.2.024002>
 - [13] Yamane, W., Westly, D., Holland, G., Yamazawa, Y., Ito, N., Vladar, A.E., et al. (2025) Multi-Technique Reference Measurement of Critical Dimension and Shape for Model Validation in Scanning Electron Microscopy. *Metrology, Inspection, and Process Control XXXIX*, Vol. 13426, 134260T. <https://doi.org/10.1117/12.3046309>
 - [14] Zuiderveld, K. (1994) Contrast Limited Adaptive Histogram Equalization. In: Heckbert, P.S., Ed., *Graphics Gems*, Elsevier, 474-485. <https://doi.org/10.1016/b978-0-12-336156-1.50061-6>
 - [15] Emanuel, M., Hafezipour, S., Roser, W., Blagojevic, A., Maniscalco, M., Mahyari, P., et al. (2026) SEM 3D Reconstruction: A Deep Learning Approach Using Adaptive Masking and Multi-Angle Disparity Fusion. *Microscopy and Microanalysis*, **32**, ozag053.324. <https://doi.org/10.1093/mam/ozag053.324>
 - [16] Roy, S., Meunier, J., Marian, A.M., Vidal, F., Brunette, I. and Costantino, S. (2012) Automatic 3D Reconstruction of Quasi-Planar Stereo Scanning Electron Microscopy (SEM) Images. 2012 *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Diego, 28 August-1 September 2012, 4056-4059. <https://doi.org/10.1109/embc.2012.6346932>
 - [17] Wang, Z., Bovik, A.C., Sheikh, H.R. and Simoncelli, E.P. (2004) Image Quality Assessment: From Error Visibility to Structural Similarity. *IEEE Transactions on Image Processing*, **13**, 600-612. <https://doi.org/10.1109/tip.2003.819861>
 - [18] Ronneberger, O., Fischer, P. and Brox, T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab, N., et al., Eds., *Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015*, Springer International Publishing, 234-241. https://doi.org/10.1007/978-3-319-24574-4_28
 - [19] Isola, P., Zhu, J.Y., Zhou, T.H. and Efros, A.A. (2017) Image-to-Image Translation with Conditional Adversarial Networks. 2017 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, 21-26 July 2017, 5967-5976. <https://doi.org/10.1109/cvpr.2017.632>
 - [20] Lin, J., Yan, Q., Lu, S., Zheng, Y., Sun, S. and Wei, Z. (2022) A Compressed Reconstruction Network Combining Deep Image Prior and Autoencoding Priors for Single-Pixel Imaging. *Photonics*, **9**, Article No. 343. <https://doi.org/10.3390/photonics9050343>