Predicting resist pattern collapse in EUVL using machine learning

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Introduction

- Pattern collapse is influenced mainly by the geometry and mechanical properties of the pattern. Photoresist patterns with higher aspect ratios (ARs) or lower feature spacing (dense features) are prone to collapse.
- Young's modulus values for EUV resists can be much lower compared to typical polymer photoresists in DUVL [1], making the patterns less stable.
- There is an added challenge of line-width roughness (LWR) caused due to the numerous stochastic effects in EUV photoresists [2].
- The sidewall surface roughness leads to localised regions of lower aspect ratios, which render the standard collapse model ineffective.

Photoresist roughness

- A 3D line resist feature can be generated using a combination of 1D and 2D power spectral densities (PSDs) [3] by superimposing the surfaces generated on the sidewalls of rough edges.
- As training input to the CNN, the irregular 3D point cloud data is converted into 2D data using a three-dimensional modified Fisher Vector (3DmFV) [5]

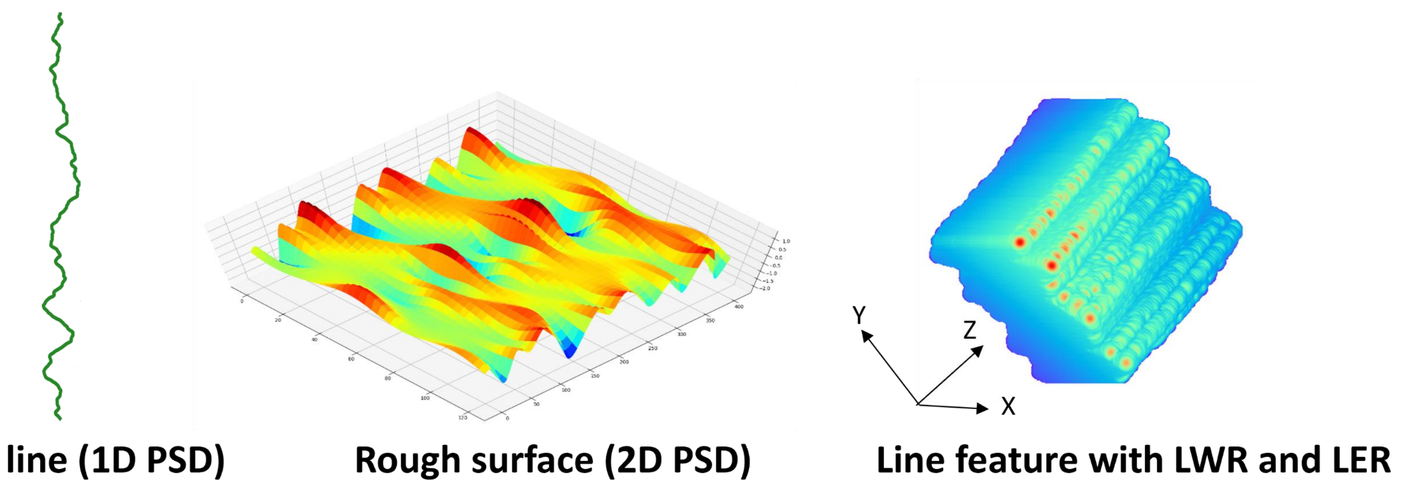

***Figure 1:** Left: A rough line is generated using a 1D PSD (left) and a 2D PSD (centre) Right: A combination of both the rough lines and rough surfaces generates a line feature with LER and LWR.*

- Training data that captures the stochastic effects influencing resist profiles is generated for orthogonal and hexagonal pillar arrangements.
- The discretization along the height is used to vary the cross-sectional diameters creating undercut profiles in order to mimic the feature roughness seen in experimental data.

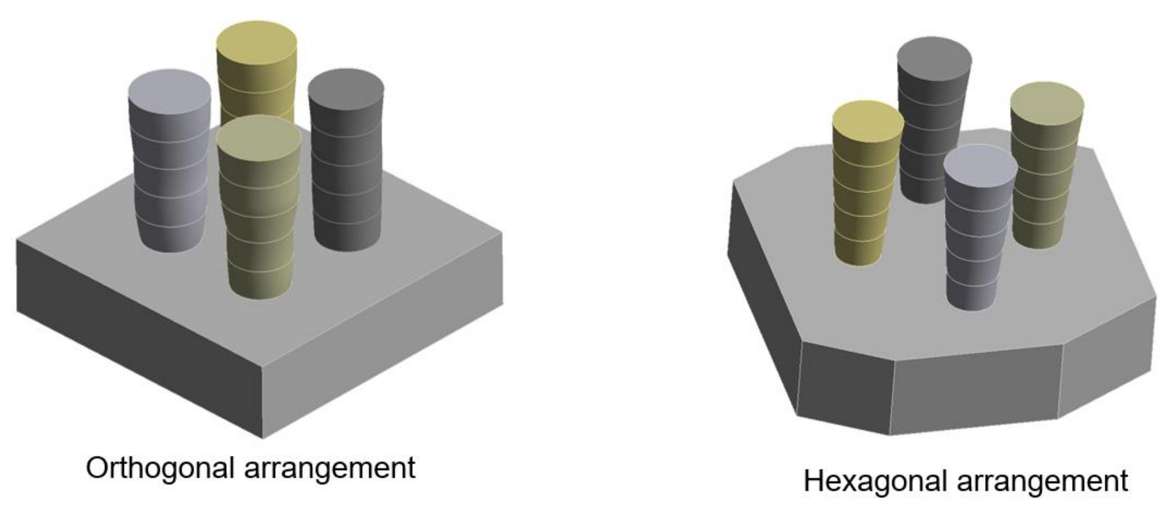

***Figure 2:** Three-dimensional representations of undercut pillars in an orthogonal arrangement (left) and a hexagonal arrangement (right)*

Data generation

- The 3DmFVs are given their corresponding labels based on the interpolation of the cross sections in combination with a graph neural network (GNN) [4].
- The GNNs predicted the individual cross-sectional displacement fields that constitute a given line feature and were validated using rigorous FEM simulation data.

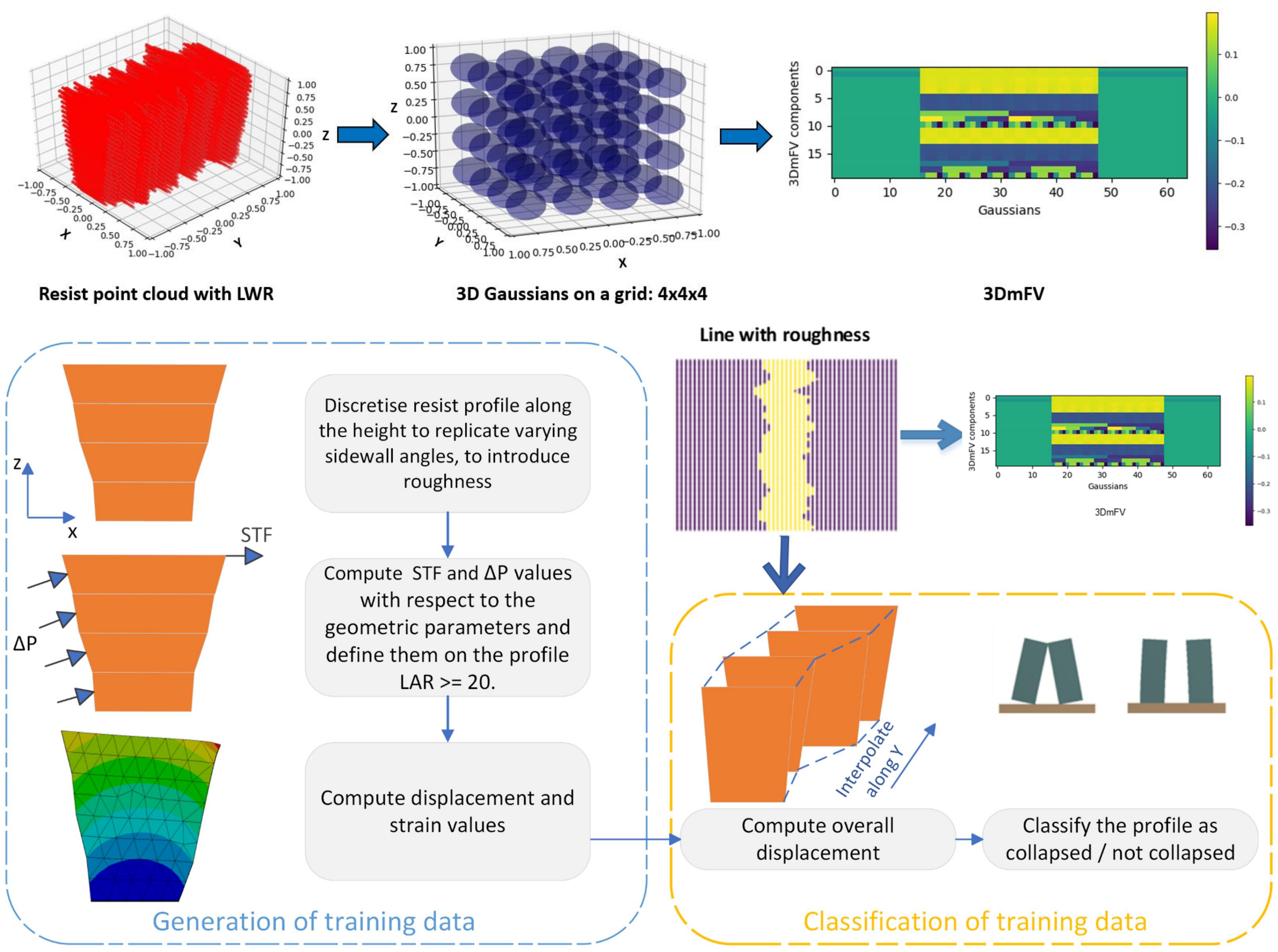

***Figure 3:** Top: computation of 3DmFVs from point clouds. Bottom: generation of training data and classification based on FEM simulations.*

Collapse prediction & results

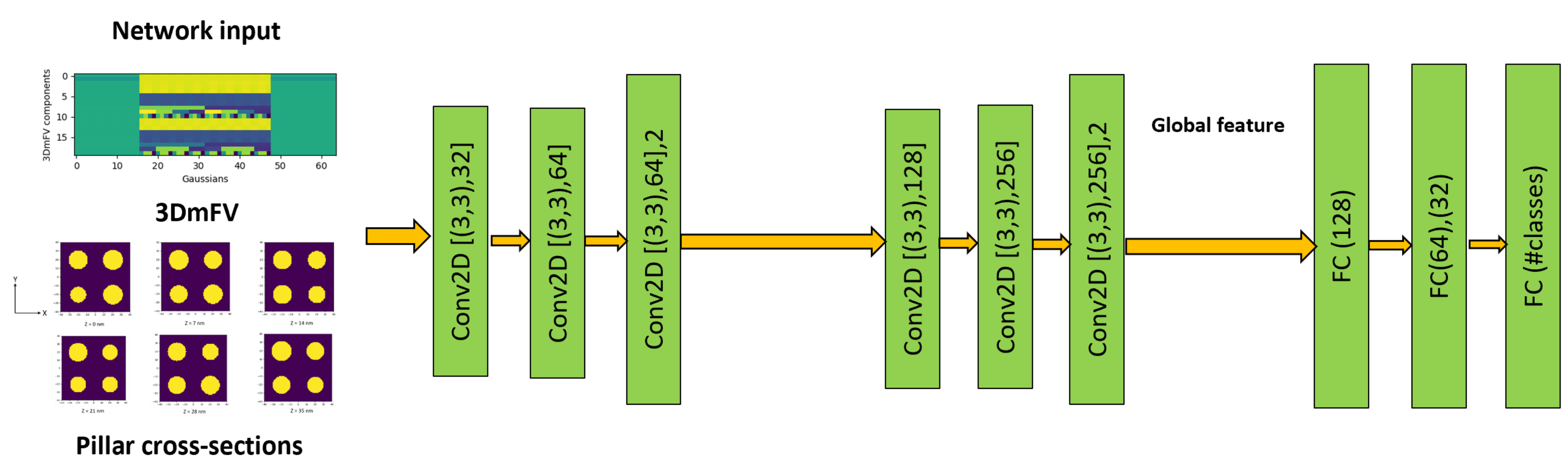

***Figure 4:** CNN architecture for the prediction of collapse probabilities in lines and spaces (L/S) and pillar use cases.*

- The overall prediction accuracy of the network is 86 % for L/S and 97 % for pillars.

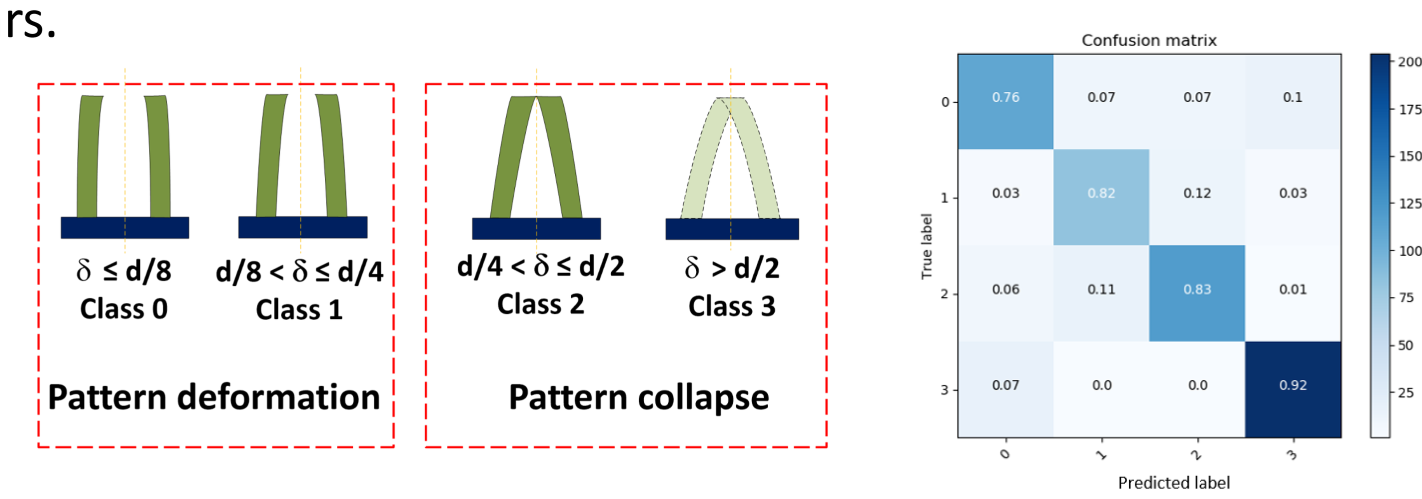

***Figure 5:** Left: collapse classification. Right: confusion matrix for a L/S use case*

- Network prediction accuracy is much better for cases where collapse is most likely to occur and lower in other cases, since the 3DmFV can detect feature densities quite well.

Conclusion

- Deformation simulations using FEM to predict collapse are slow and complicated.
- Pattern collapse probabilities for simulated profiles can be predicted in a few seconds using ML
- Resist material properties, feature density and profile shape influence collapse.

References

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