

# Miop: a modular pipeline for 3D reconstruction from scanning electron microscope images

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**DOI:** 10.21105/joss.08457

#### **Software**

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Submitted: 30 April 2025 Published: 11 September 2025

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## Summary

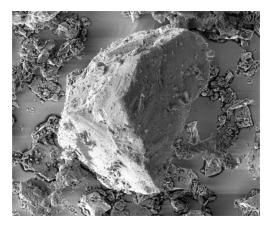
Powdered materials are ubiquitous in nature and widely used in industries such as food, cosmetics, and construction. These materials consist of small grains with a broad size and shape distribution, typically in the micrometer range. Understanding their microscale behavior requires accurate geometric characterization. Scanning electron microscopy (SEM) provides a fast and accessible method for imaging powdered materials at this scale. By leveraging the tilt capabilities of the microscope, along with feature-matching algorithms, it is possible to reconstruct the three-dimensional (3D) shape of individual grains.

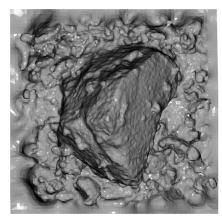
We introduce Miop, a modular pipeline for 3D reconstruction from SEM images. Miop implements key steps of a 3D reconstruction workflow, including feature matching, estimation of (intrinsic and extrinsic) camera parameters, and point cloud reconstruction. It models the image generation process using a scaled orthographic projection and can incorporate microscope metadata, such as stage tilt and rotation angle. Designed for flexibility, Miop is easily extensible and modifiable, providing researchers with a practical tool for 3D reconstruction of powdered materials. An example of a typical reconstruction generated by Miop is illustrated in Figure 1.

## Statement of need

3D reconstruction from SEM images is a well-studied problem (Eulitz & Reiss, 2015; Tafti et al., 2015; Töberg & Reithmeier, 2020). However, to the best of our knowledge, there are no open-source tools specifically designed for 3D reconstruction from SEM image sets that offer the flexibility and modularity required for research use. General-purpose 3D reconstruction libraries such as COLMAP (Schonberger & Frahm, 2016) are tailored to standard perspective cameras and do not support the specific imaging geometry of electron microscopes. Other approaches (Töberg & Reithmeier, 2020) are limited in scalability or are not designed to be extended for custom workflows. Despite active research in 3D reconstruction and SEM imaging, we are not aware of any new software addressing these specific limitations in recent years.







**Figure 1:** Typical Miop input and output. Left: a sample SEM image of a cement grain. Right: reconstruction using Miop.

# **Brief software description**

The reconstruction problem is formulated as a projection of a 3D scene onto the image plane. Under a scaled orthographic camera model, the projection of a single three-dimensional point is given by:

$$\underbrace{\begin{bmatrix} k & 0 & 0 \\ s & k & 0 \end{bmatrix} R}_{C} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \underbrace{\begin{bmatrix} x_{p,1} \\ y_{p,1} \end{bmatrix}}_{W}$$

where k defines the scaling, and s is a skew parameter. The rotation matrix R is determined by the tilt angle and axis of the microscope stage. This model accurately describes the image generation process in SEM at high magnification, as discussed in Töberg & Reithmeier (2020).

The matrix C fully determines both the intrinsic and extrinsic parameters of the camera. If C and W are known, the system can be solved using methods such as least squares. When the axis of rotation of the microscope stage is known, C can be reconstructed from the microscope metadata. For microscopes with eucentric capabilities, a horizontal rotation axis can be assumed, allowing the rotation matrix R to be recovered from the tilt angles. Furthermore, the scaling factor k is determined by the magnification, and the skew parameter s can be assumed to be zero.

If metadata are unavailable or unreliable, the intrinsic and extrinsic parameters of the camera can be estimated using the factorization method proposed by Poelman and Kanade (Poelman & Kanade, 1993; Tomasi & Kanade, 1992). This approach factorizes W into two matrices using singular value decomposition (SVD):

$$W = \left(U\Sigma^{\frac{1}{2}}\right)\left(\Sigma^{\frac{1}{2}}V^T\right) = \hat{C}\hat{S}$$

allowing  $\hat{C}$  and  $\hat{S}$  to be computed efficiently. However, this decomposition is not unique, as any invertible 3x3 matrix Q and its inverse can be inserted between  $\hat{C}$  and  $\hat{S}$ :

$$W = \hat{C}QQ^{-1}\hat{S}$$

To recover Q, we solve the following linear system (Poelman & Kanade, 1993; Tomasi & Kanade, 1992):



$$\begin{split} \hat{i}_f^T Q Q^T \hat{j}_f &= 0 \\ \hat{j}_f^T Q Q^T \hat{j}_f - \hat{i}_f^T Q Q^T \hat{i}_f &= 0 \end{split}$$

where  $\hat{i}_f$  and  $\hat{j}_f$  are the rows of the camera matrix  $\hat{C}_f$ . Since  $QQ^T$  is a 3x3 symmetric matrix, it has six unique entries. We therefore need at least 3 different images to recover  $QQ^T$ . Moreover, to avoid the trivial solution ( $\hat{i}_f=0$  and  $\hat{j}_f=0$  for all f), the scaling of the first camera is set to one (Poelman & Kanade, 1993):

$$\hat{i}_1^T Q Q^T \hat{i}_1 = 1.$$

Q is then obtained from the eigendecomposition of  $QQ^T$ . The method of Poelman and Kanade (Poelman & Kanade, 1993) thus allows computing the camera positions from W.

The matrix W is obtained through feature matching. Our pipeline currently uses the RoMa model (Edstedt et al., 2023), but users can easily integrate other algorithms if better suited to their specific applications.

## **Usage and Documentation**

The code is hosted on GitLab: <a href="https://gitlab.com/cmbm-ethz/miop">https://gitlab.com/cmbm-ethz/miop</a>. Installation and usage instructions are available in the README.md file. An example Jupyter notebook is provided to visualize intermediate steps of the reconstruction.

## **Acknowledgments**

Part of the implementation of the scaled orthographic model is based on the code of Toeberg (Töberg & Reithmeier, 2020), available at https://github.com/Karido/3D-SEM/.

The authors acknowledge the Swiss National Science Foundation for financial support under grant 200021\_200343.

The authors gratefully acknowledge the Scientific Center for Optical and Electron Microscopy (ScopeM) of ETH Zurich for providing helpful technical advice and support. The authors thank Christian Zaubitzer (ScopeM, ETH Zurich, Switzerland) for his assistance in image generation. The authors also thank Dr. Zuria Bauer and Dr. Sandro Lombardi for useful discussions during the method development.

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