

Toward Automated Plasma Focus Ion Beam Instrument Calibration for Materials Processing

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Introduction

To accelerate the transition to autonomous focused ion beam (FIB) microscopy, we require an **objective figure of merit (FOM)** for assessing calibration. For our purposes, these FOMs related to beam astigmatism, quad, and focus. Intelligent calibration integrated into scripted workflows will **enable fully automated sample preparation workflows** that produce **higher quality samples with less operator time**.

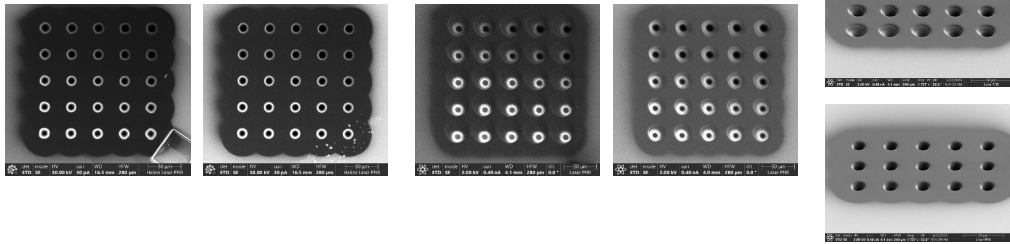


Figure 1: Out of versus in calibration characteristics; astigmatism (left), quad (middle), and focus (right)

Methods

- We have implemented convolutional neural network (CNN) model to analyze automated spot burns and **determine a FOM for each burn**.
- Utilized pretrained microscopy weights from NASA codebase

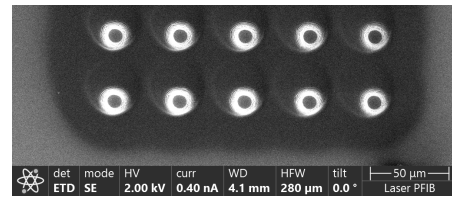


Figure 2: Spot burns cut into Si by our integrated calibration software

Custom scripts have been written to:

- ✓ Create and evaluate **FOM for astigmatism calibration**
- ✓ Create Patch Transformation to **increase training and validation dataset size**

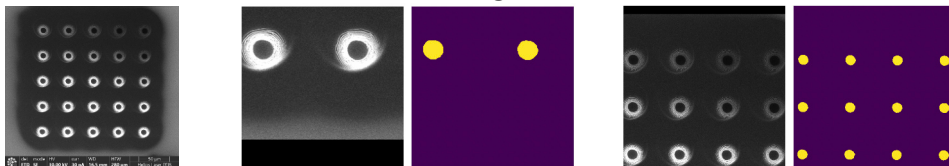
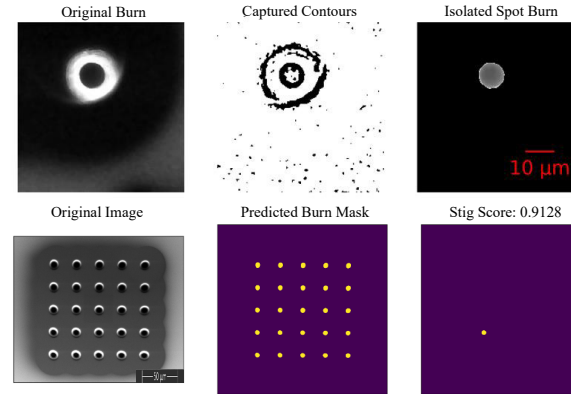


Figure 3: The original SEM 1024x1024 image (left), a script curated 256x256 training patch and its mask (middle), and the 512x512 validation patch and its mask (right)

Results and Discussion

Spot Burn Analysis



Computer vision identifies and isolates circular centers (pierces) in SEM image for visualization of objective.

UNet++ is given SEM image and **outputs mask of burns** which is then **processed based on predefined FOMs**.

Figure 4 (top): The original SEM image (left), a script identified and edited version of the spot burn (middle), and the identified pierce (right)

Figure 5 (bottom): The altered SEM image from script (left), model-identified burns (middle), and best burn (right)

Model Training

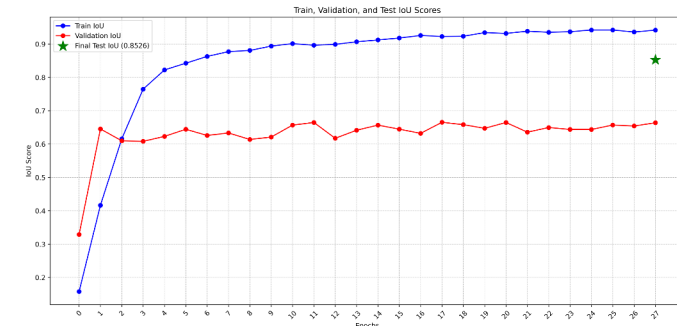


Figure 6: Line plot describing relation of IoU score over epochs for training and validation data, as well as final test IoU

Patch training results in **high Intersection over Union (IoU)** on training and test data.

- IoU difference between train and validation may indicate overfitting

Future Work

- Quantify FOMs for focus and quad
- Integrate FOMs into calibration and sample preparation scripts
- Further tune CNN Model to include K-Fold Cross Validation and more data

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References

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