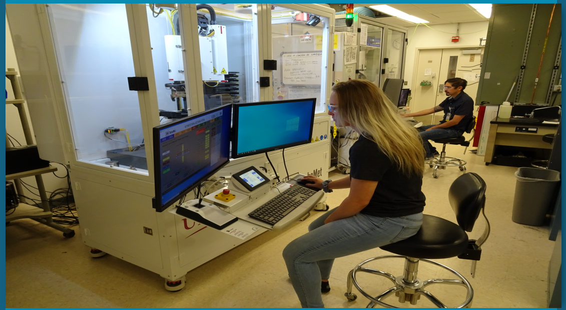
SAND2022-2525C

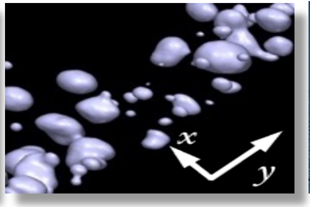
CELEBRATION AIME–TMS 150th TMS 2022 Annual Meeting & Exhibition SINCE 1871

FEBRUARY 27—MARCH 3, 2022
ANAHEIM, CALIFORNIA, USA

Sandia National Laboratories

Improving Autonomous Data Collection By Run-to-Run Control Algorithm as Applied to a RoboMet Mechanical Serial-Sectioning System





PRESENTED BY

Damian Gallegos-Patterson[1,2]

Andrew Polonsky[1], Jonathan D. Madison[1], Claus Danielson[2]

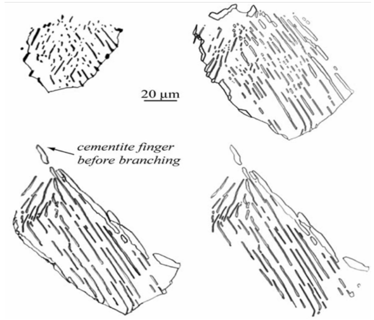
1. Sandia National Laboratories
2. The University of New Mexico

Outline

- History of Mechanical Serial-Sectioning
- Robo-Met.3D® at Sandia National Laboratories
- Motivation
  - Consistent slice thickness
  - Reduce operator intervention
  - Autofocus error
- Current Work
  - Model of system dynamics
  - Optimization problem
  - Run-to-run control algorithm
- Results
  - Simulation results
  - Physical system test results
- Conclusion & Future work

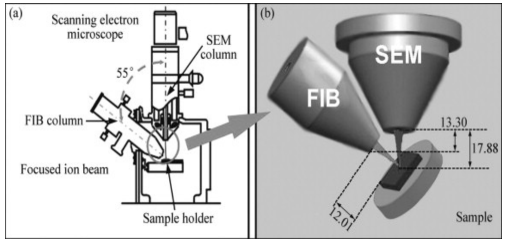
AUTOMATED MECHANICAL SERIAL-SECTIONING

O. Forsman (Jern-Kontorets Ann, 1918, vol. 102)
M. Hillert and N. Lange (unpublished, 1962)



1918 / 1962

T. Sakamoto et al., (Japanese J. of Appl. Physics, 1998, vol. 37, no. 1)



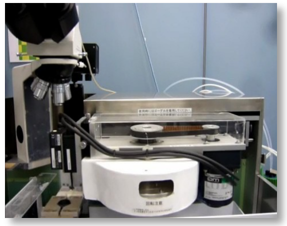
1998

Spowart, Mullens, Puchala
(JOM, 2003, vol. 55)

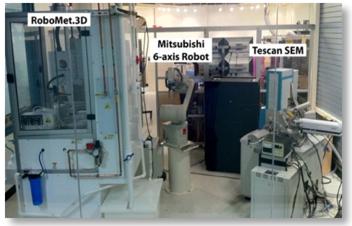
2003

3DMS
(The First International Conference on 3D Materials Science, 2012)

Adachi et al.

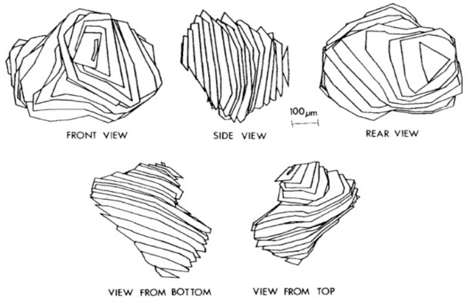


Uchic et al.



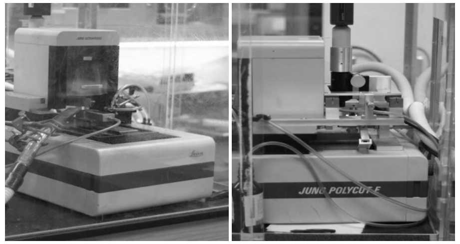
2012

1991



Hull et al, (Mater. Char, 1991)

2001



Alkemper and Voorhees
(J. Microscopy, 2001, vol. 201, no. 3)

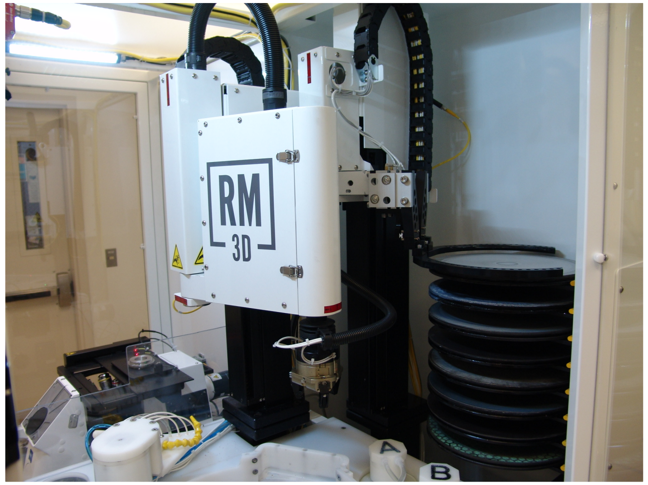
2008

Robo-Met.3D® Version 2 commercialized

2012

Echlin et al.
(Rev. Sci Instruments, 2012, vol. 83, 2012)

Robo-Met.3D® at Sandia National Laboratories



Robo-Met.3D® at Sandia National Laboratories

System Components

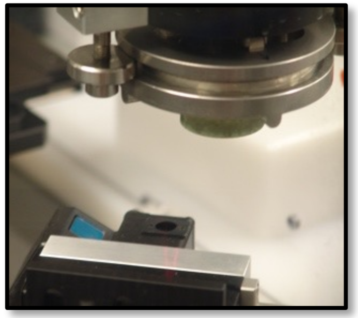
- Automated robotic polisher with variable polishing wheel
- Automated high-resolution inverted microscope with montage imaging
- Dual internal ultrasonic cleaning stations
- Three internal compact chemical etching stages
- External operator station for real-time observation of data collection

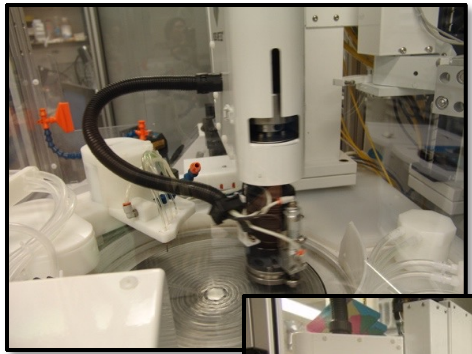
Customized Components

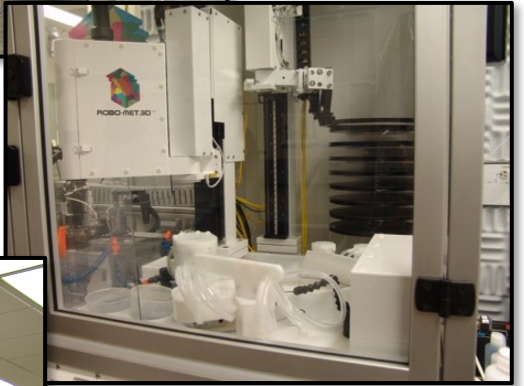
- 8+ Multi-platen polishing surface cassette interchange system
- Imaging in brightfield, darkfield & polarized light modes
- 3 additional turreted microscope objective positions available
- Added monitor(s) for customer viewing of data collection real-time
- Viewport for in-situ verification of polishing load
- Laser triangulation for high precision material removal measurement
- Pre-set in-line locations for additional sample surface diagnostics
- Original LabView program w/GUI for real-time analysis of data collection

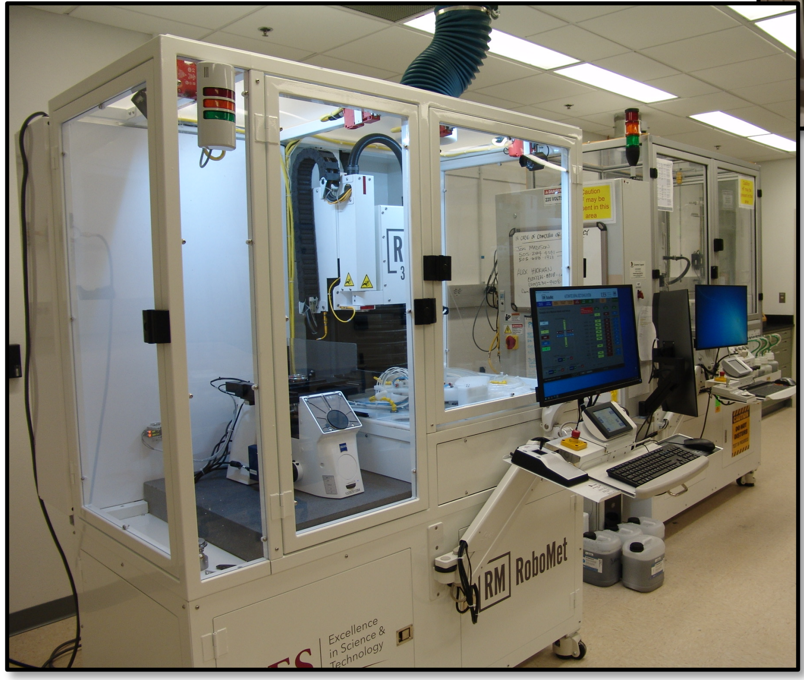
Benefits

- Sectioning rates up to 100 times the baseline manual process
- Automated handling eliminates variability caused by human handling
- Precise repeatability for imaging location, illumination, contrast, exposure & feature focus
- Demonstrated repeatable sectioning thicknesses down to 1.0 μm per slice
- Documented slice rates of up to 20 slices per hour
- Applicable to high and low strength metals (e.g. Al, Cu, Ti, Steel, Ni), composites, ceramics, foams, and bone







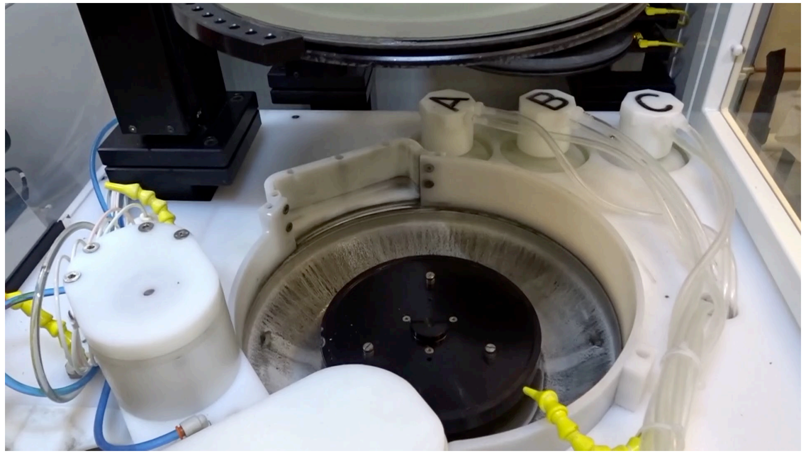


Imaging & Resolution

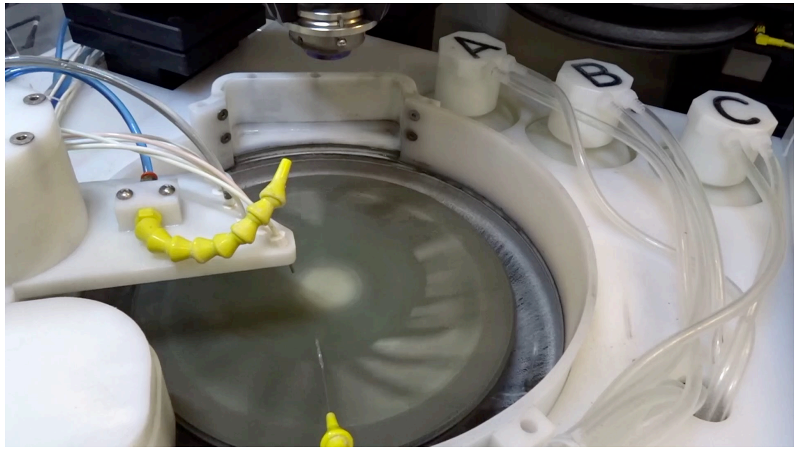
Multiple optical objectives in a rotating turreted mount

5X	---	2.10 um/pixel
10X	---	1.05 um/pixel
20X	---	0.53 um/pixel
50X	---	0.21 um/pixel

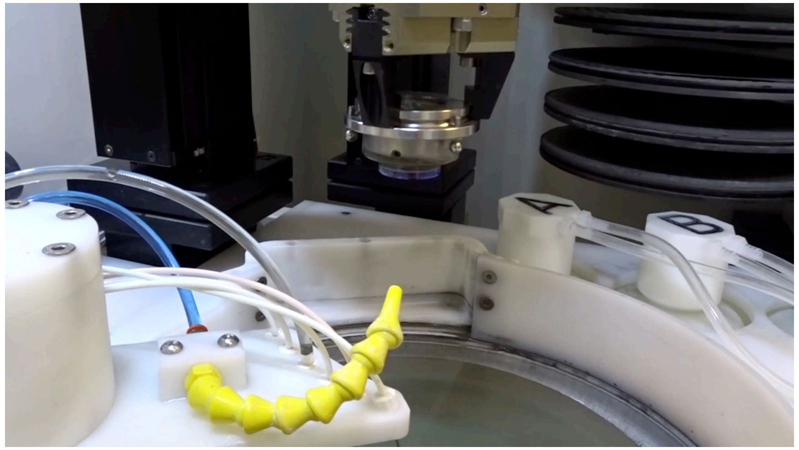
Robo-Met.3D® at Sandia National Laboratories



Platen Load

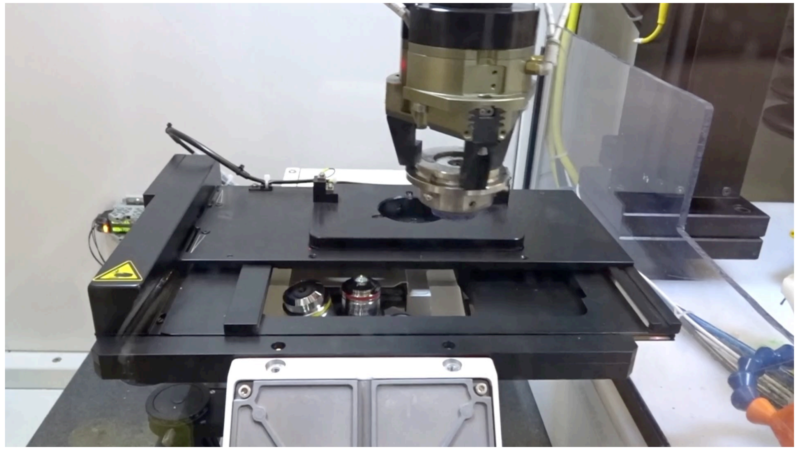


Sample Polish



Sample Rinse

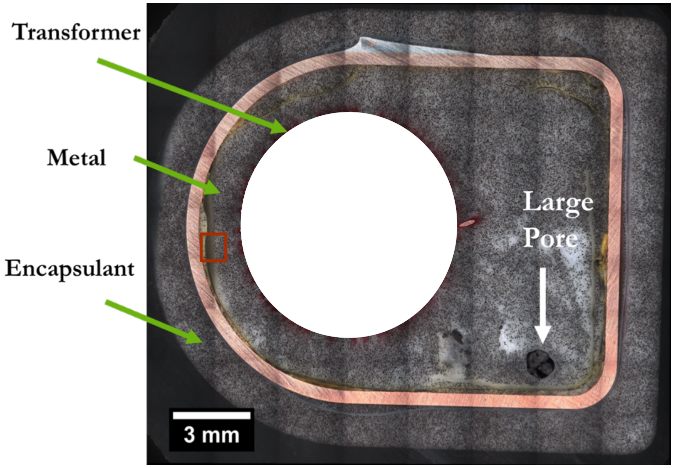
Ultrasonic Bath & Air Dry



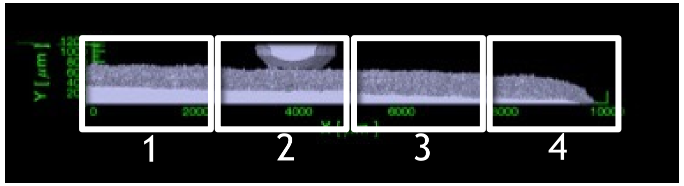
Microscope Load

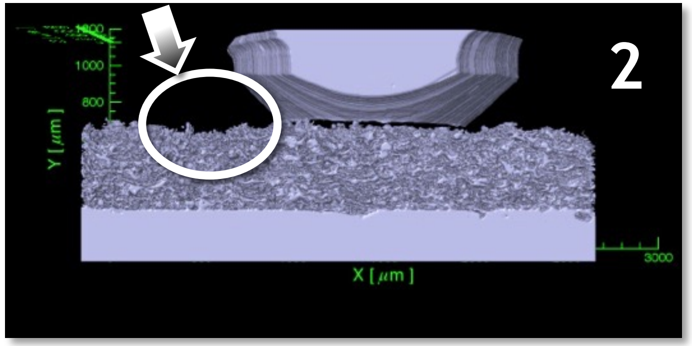
Montage Imaging

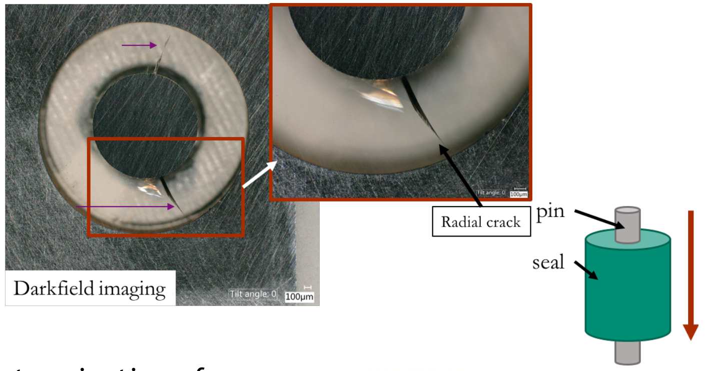
Robo-Met.3D® at Sandia National Laboratories



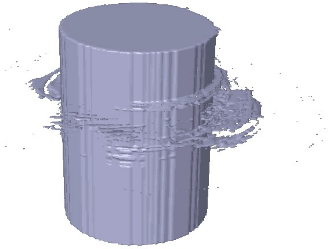
Identification of manufacturing defects in multi-material parts *

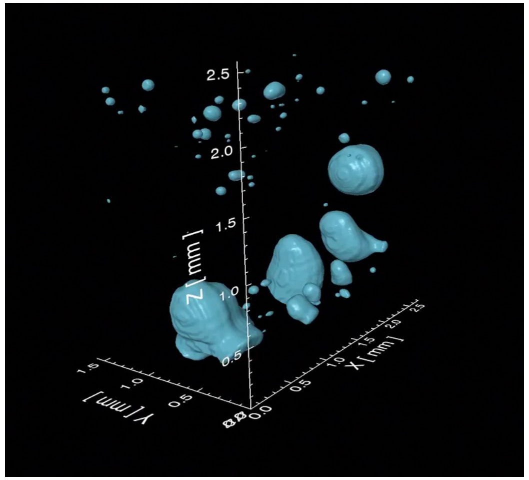




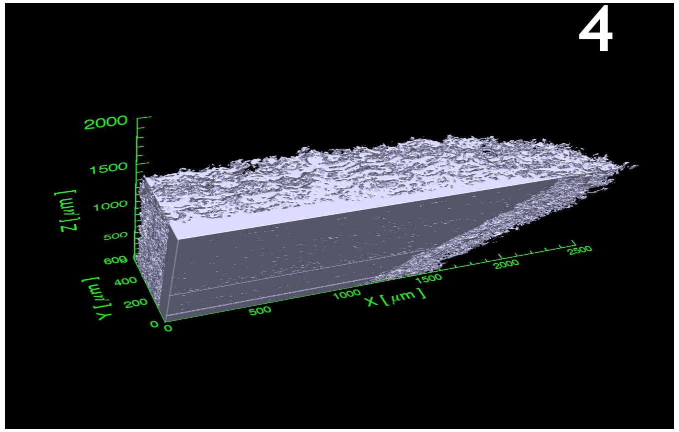


Determination of crack size, severity and depth in glass-to-metal seals for connectors



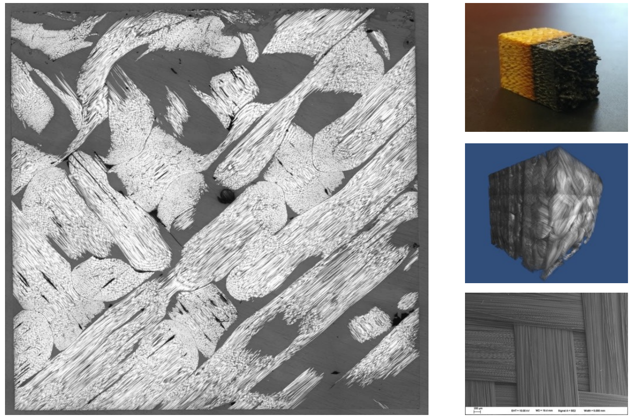


Explicit quantification of location, size and morphology of porosity in laser welds



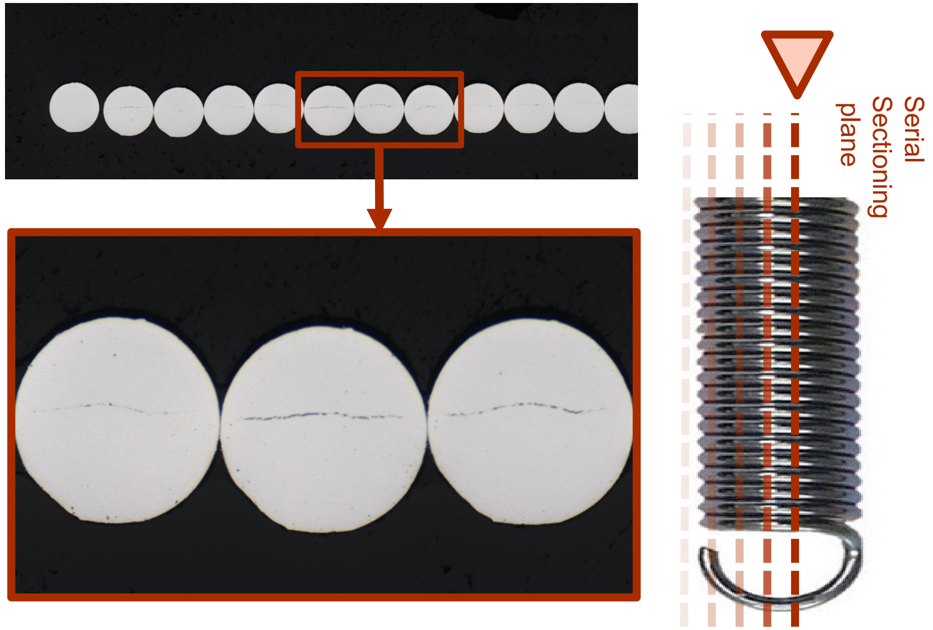
Subsurface damage in thermal spray coatings *

Brake, Hall, Madison Surface & Coating Technology 310 (2017)



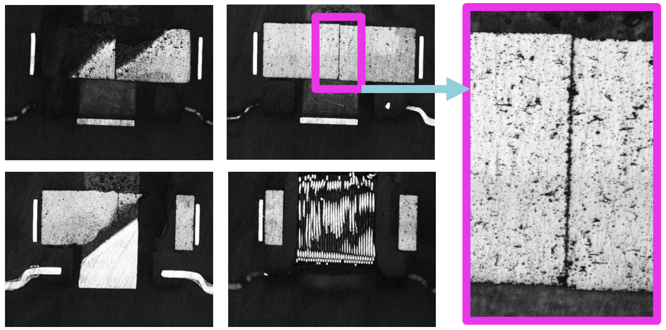
weave pattern consistency, voiding and resistance to charring in fiber-reinforced-composites*

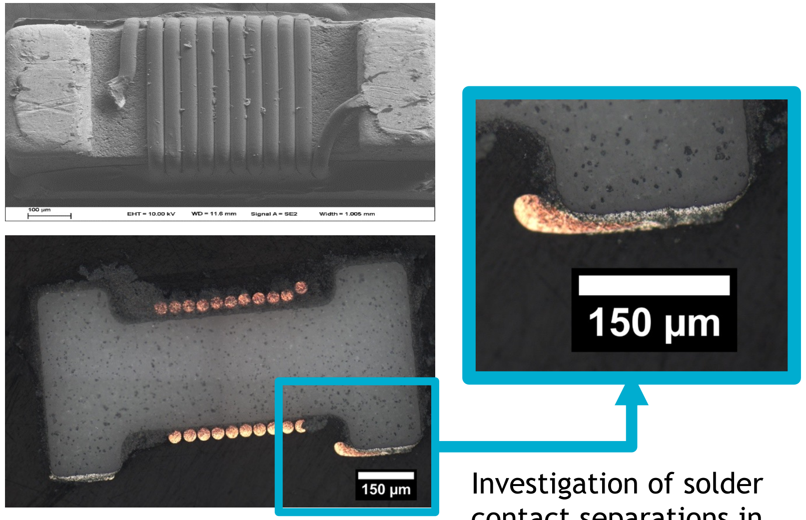
Robo-Met.3D® at Sandia National Laboratories



Identification of crack length, width and chirality in pre- and post- heat-treatment springs *

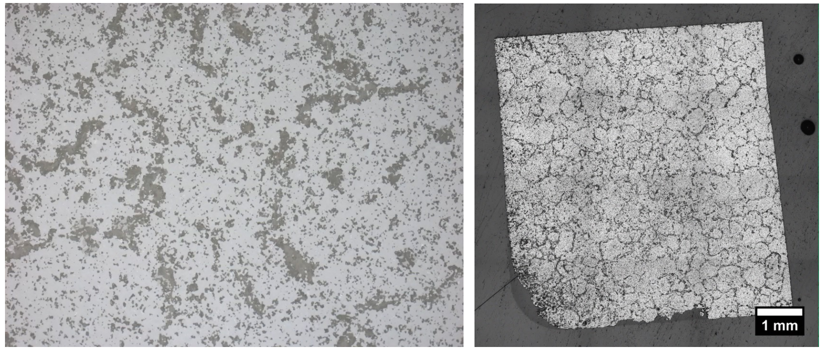
Defect identification and through-thickness inspection of a multi material component *





Investigation of solder contact separations in micro-inductors *

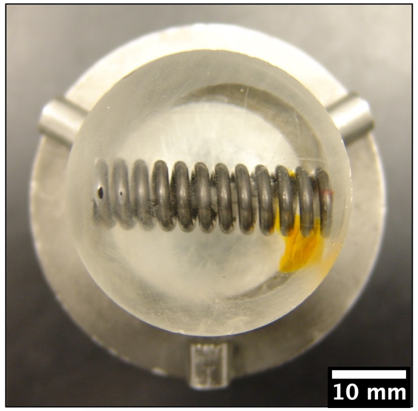
Ivanoff, Madison Advanced Materials & Processes 178 (2020)



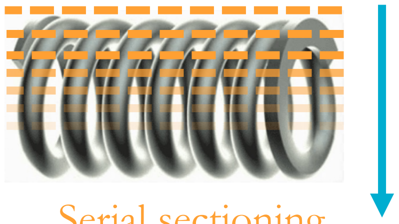
Characterization of porosity volume fraction, nearest neighbors and connectivity in Pb-Zr-Ti *

3D Reconstruction

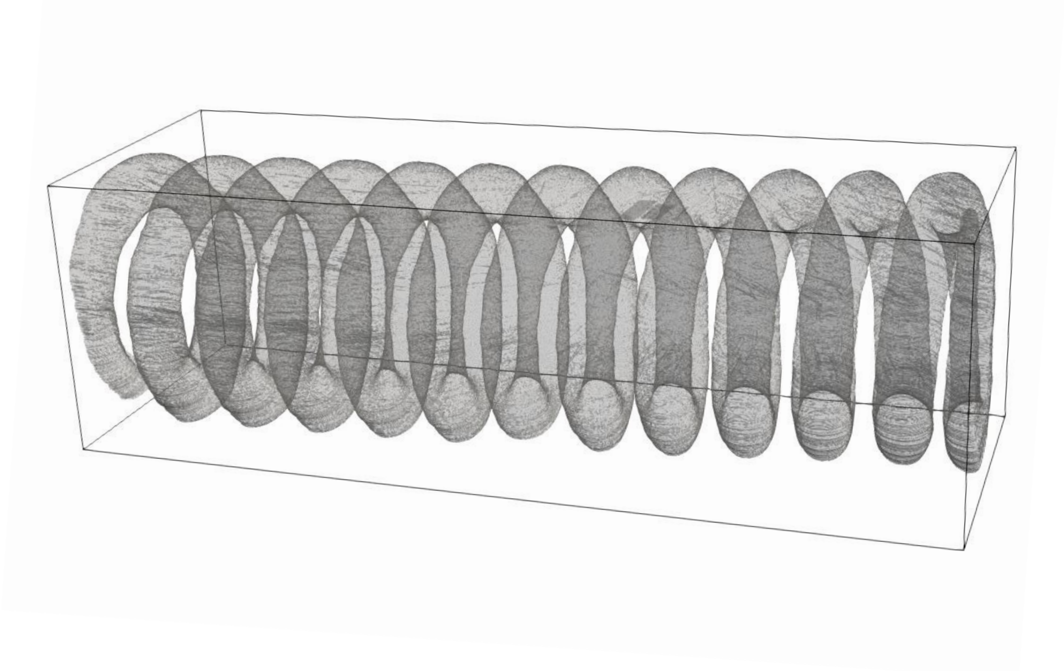
Irregular slicing thickness evident from non-circularity of spring



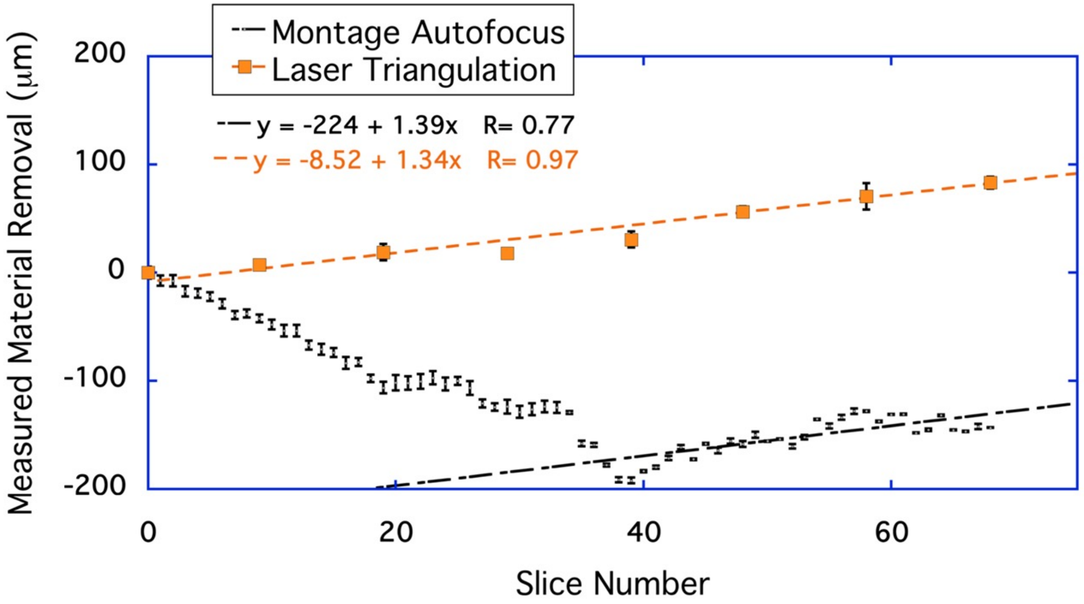
Serial sectioning direction

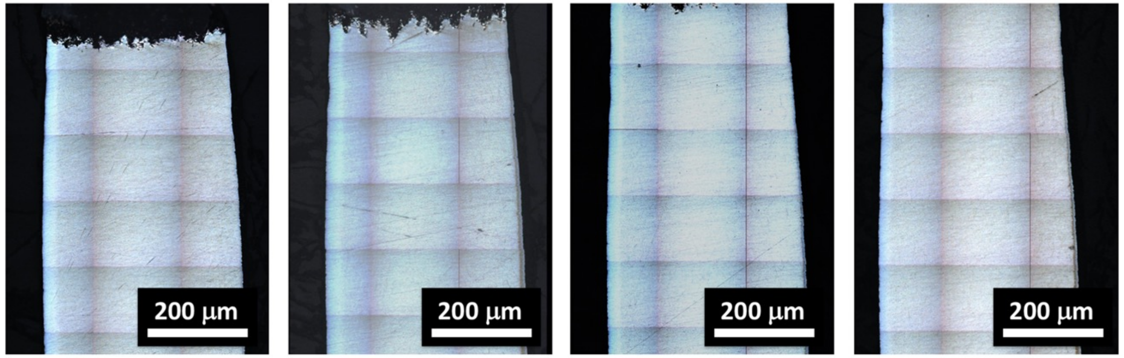


Serial sectioning plane



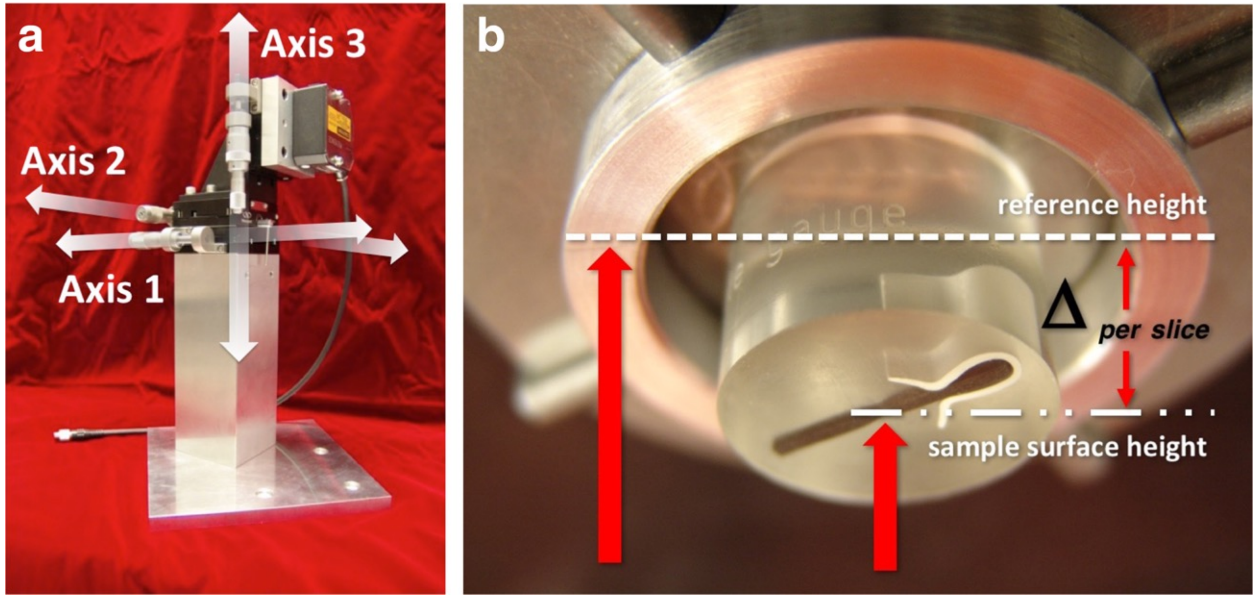
Laser Triangulation & Autofocus Error





Slice 0 Slice 20 Slice 40 Slice 60

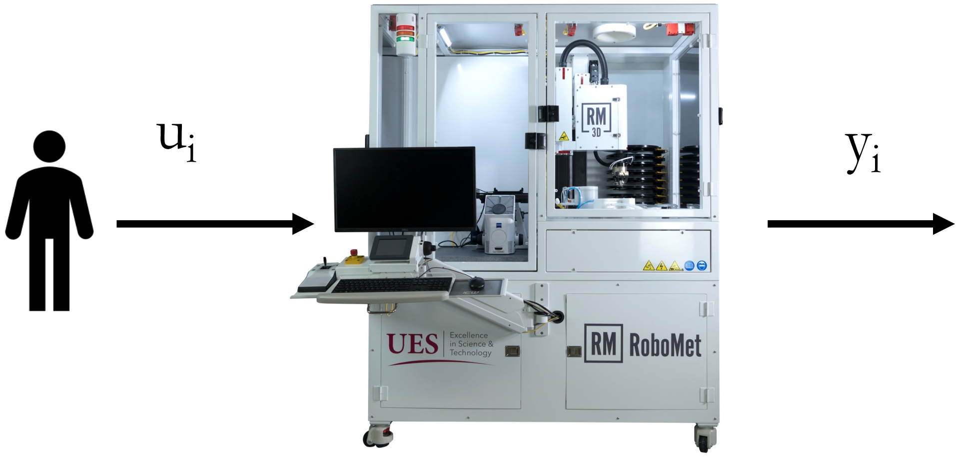
Madison, Underwood, Poulter, & Huffman IMMI (2017)



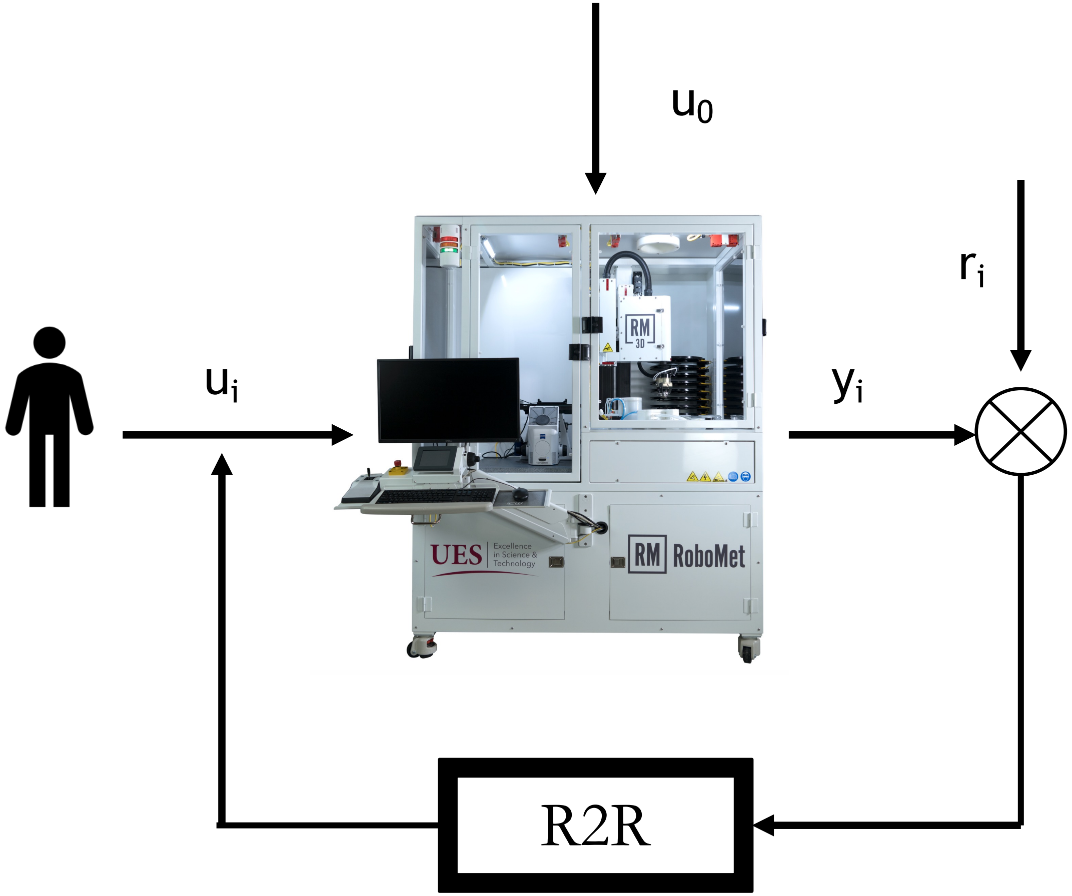
- Laser Triangulation used to accurately read slice to slice removal amount
- Provides fail safe measurements should autofocus incorrectly focus

Open Loop to Closed Loop

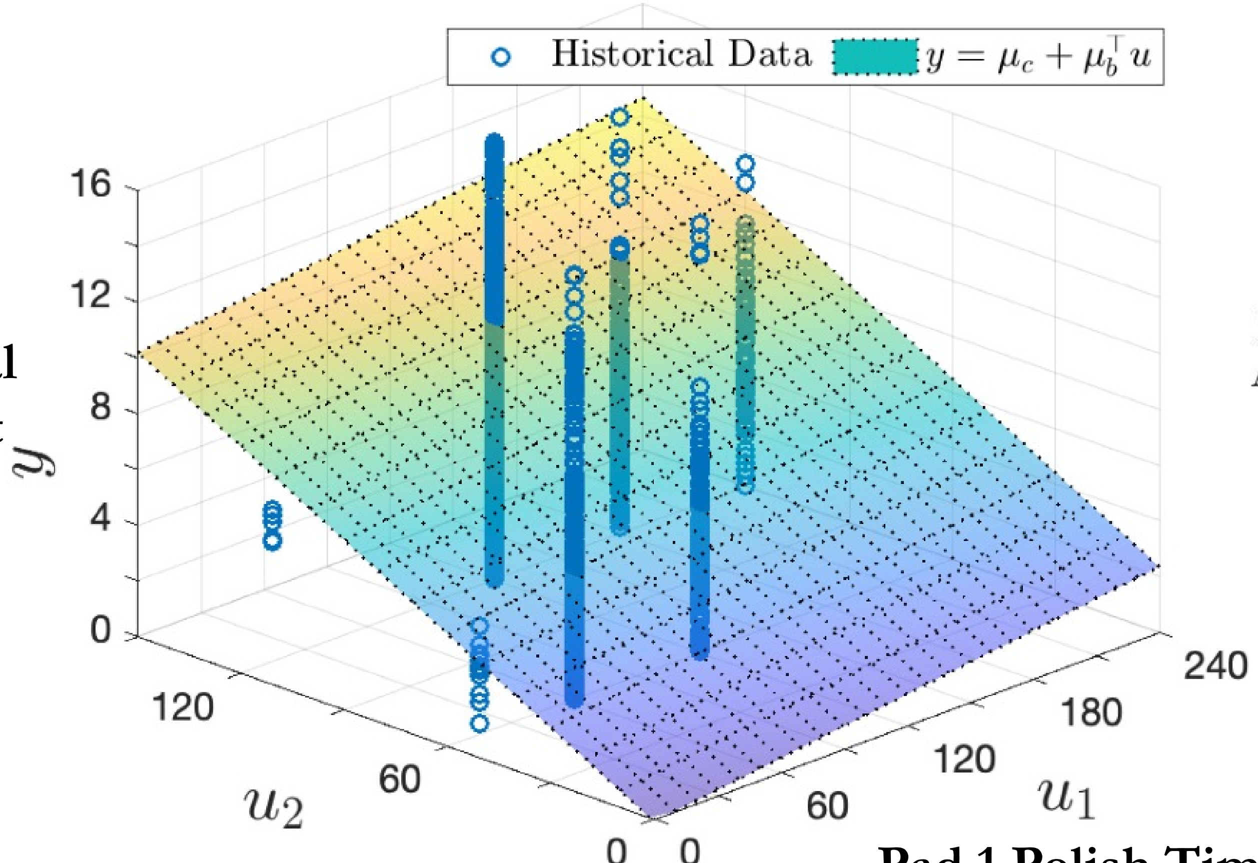
Open Loop System



Closed Loop System



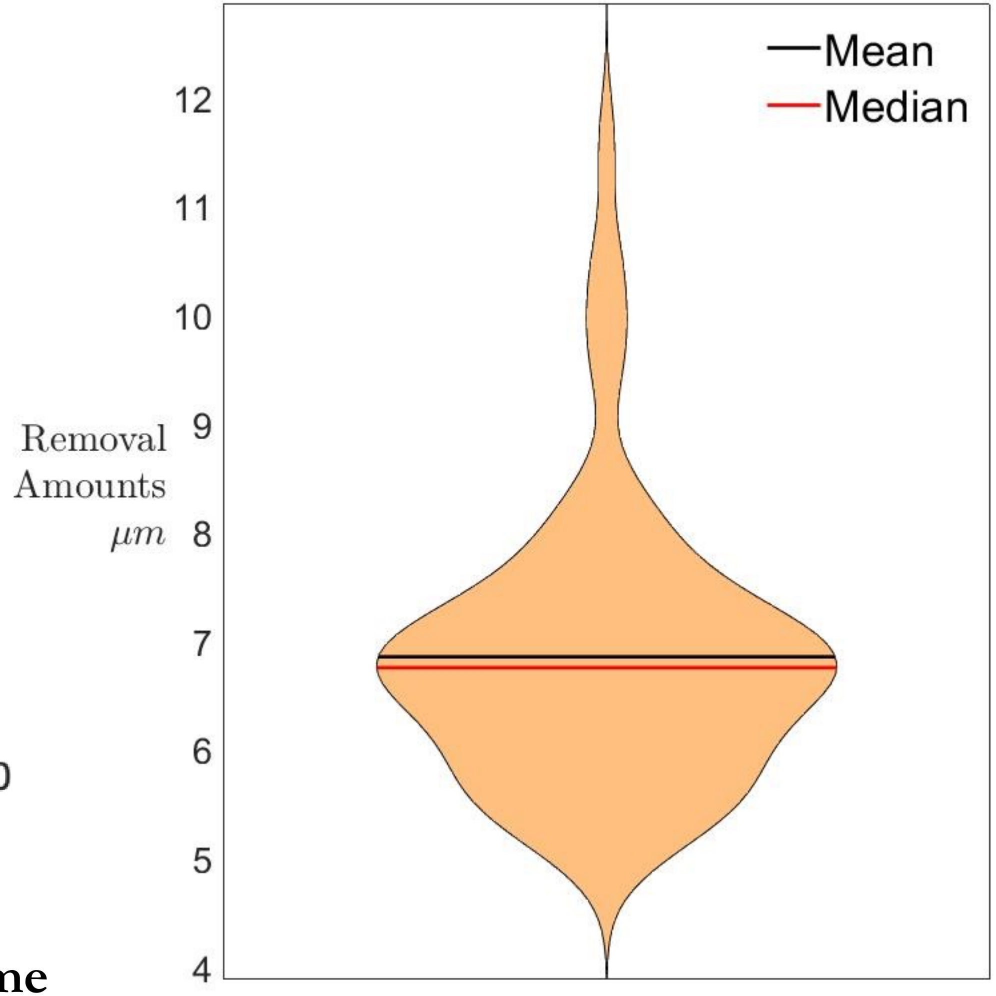
Stochastic Model and Algorithm Creation



Removal Amount (μm)

Pad 2 Polish Time

Pad 1 Polish Time

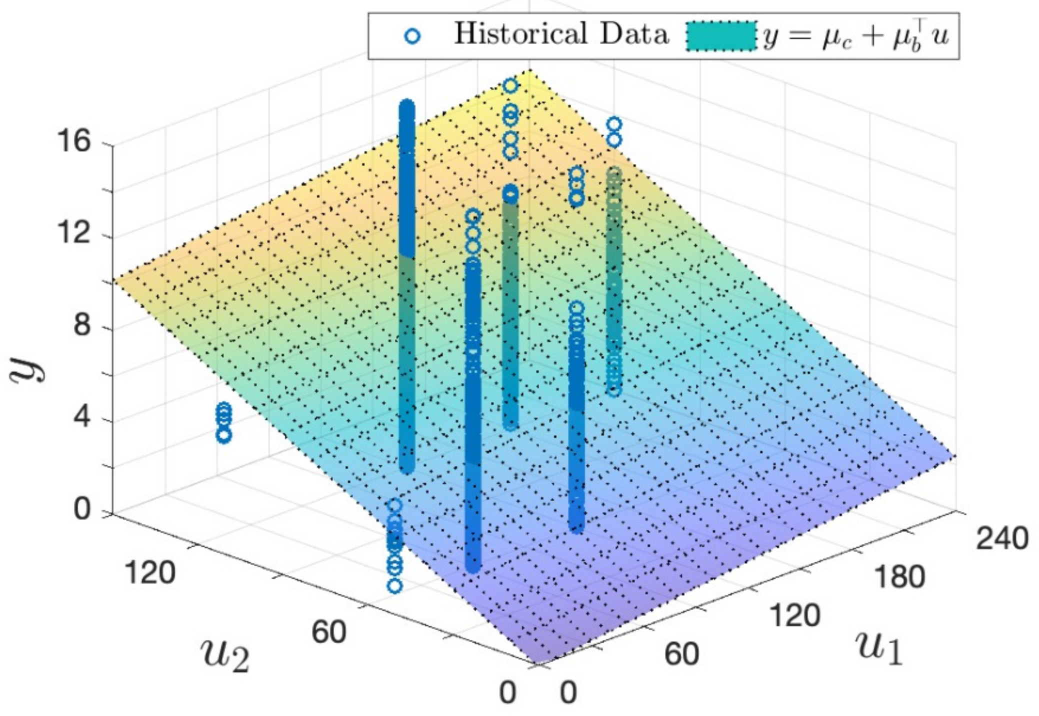


Stochastic Model and Algorithm Creation

- Linear model used for system
- Optimization problem used to minimize the variance of the output subject to the system dynamics

Linear regression model for system dynamics

$$y_i = c + b^\top u_i$$



Optimization problem

$$\begin{aligned} u_i = \; & \arg\min_{u} \; u^\top \Sigma_{bb} u + 2u^\top \Sigma_{bc} \\ & \text{s.t.} \;\; \mu_c + \mu_b^\top u_i = r_i \\ & \qquad u_i \in \mathcal{U} \end{aligned}$$

Stochastic Model and Algorithm Creation

- Optimization problem used to minimize the variance of the output subject to the system dynamics
- Run-to-run control algorithm used to consistently removal target amount

Variables	Real World Values
r_i	Target Removal Amount
u	System Inputs
μ_c	Estimated variance of output
μ_b	Estimated variance of inputs
Σ_{bb}	Estimated covariance of the inputs
Σ_{bc}	Estimated covariance of the inputs and outputs

Optimization problem

$$\begin{aligned} u_i = \ & \arg\min_u \ u^\top \Sigma_{bb} u + 2u^\top \Sigma_{bc} \\ & \text{s.t.} \ \mu_c + \mu_b^\top u_i = r_i \\ & \qquad u_i \in \mathcal{U} \end{aligned}$$

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\end{aligned}
$$

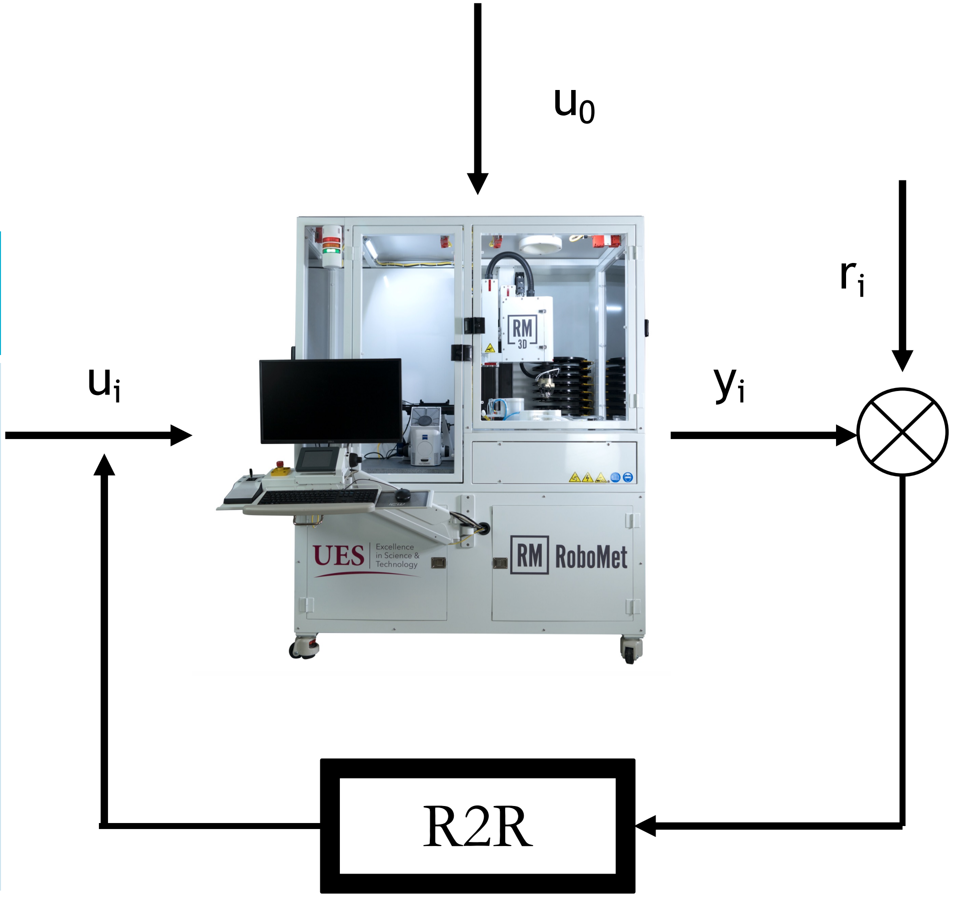
Stochastic Model and Algorithm Creation

Exponentially Weighted Moving Average

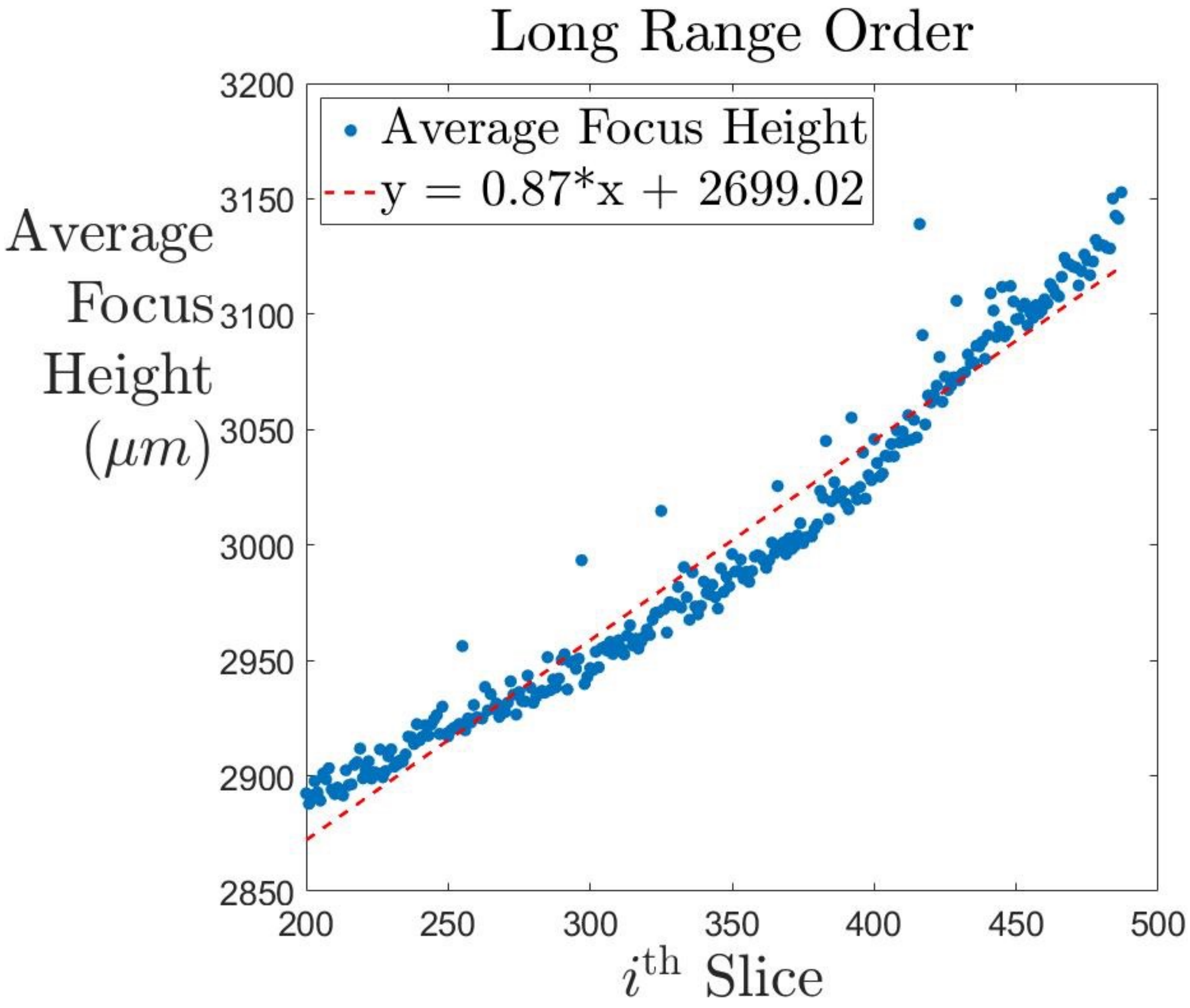
$$\mu_{c,i+1} = \mu_{c,i} + \lambda(y_i - r)$$

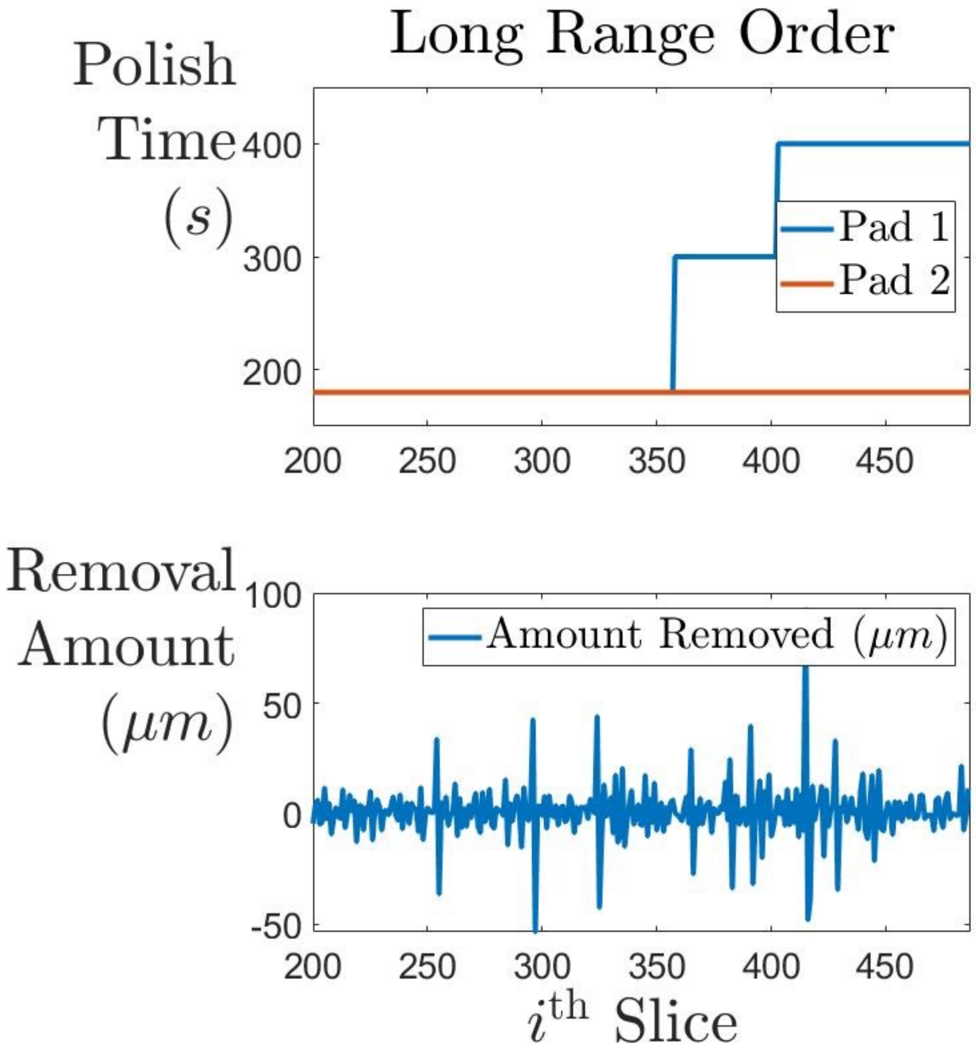
Algorithm: Optimal Run-to-Run Control

1. Implement initial recipe u_0
2. **Repeat**
3. Measure material removed y_i for *i*-th slice
4. Update EWMA drift coefficient μ_c
5. Solve optimization problem for optimal recipe u_i
6. Implement recipe u_i
7. **Until** all slices complete



Historical Sample





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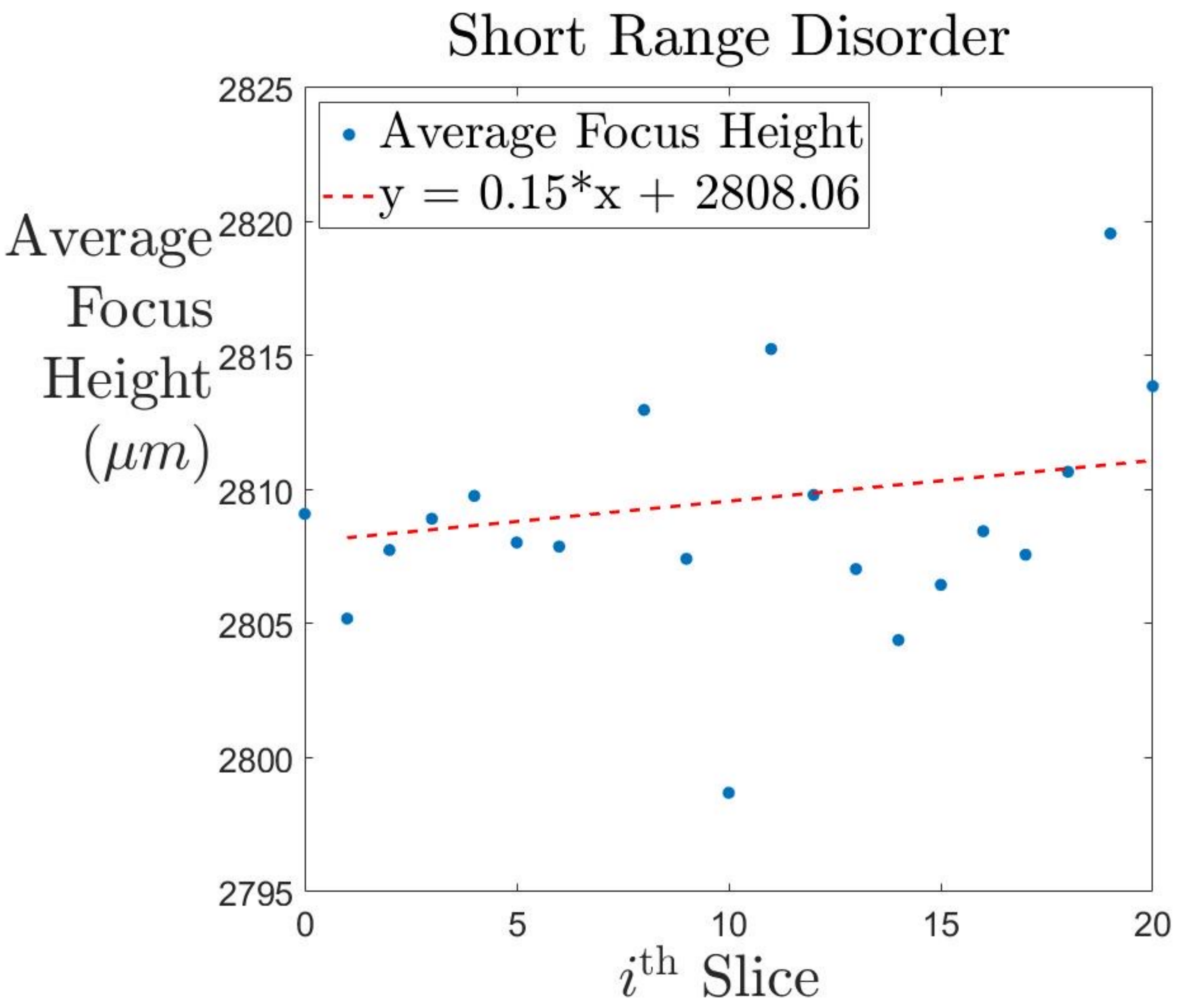
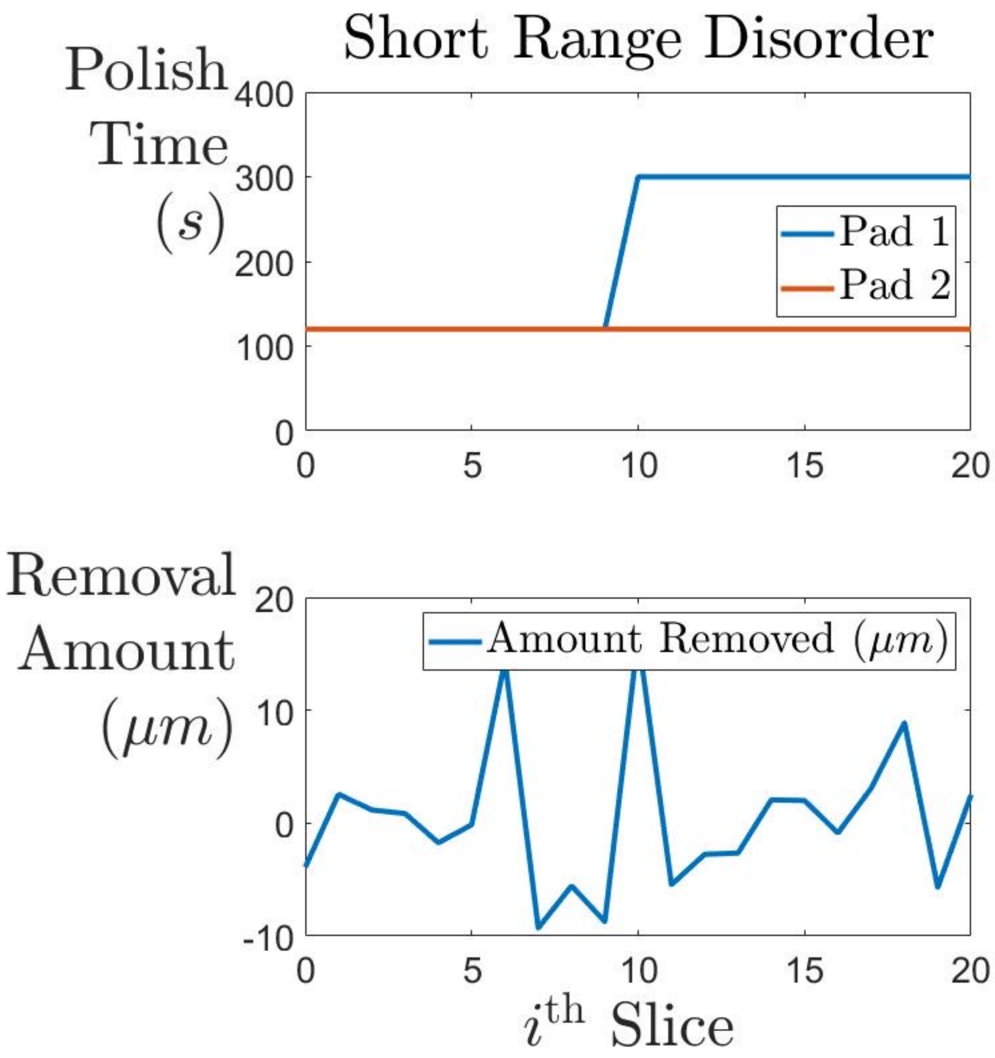
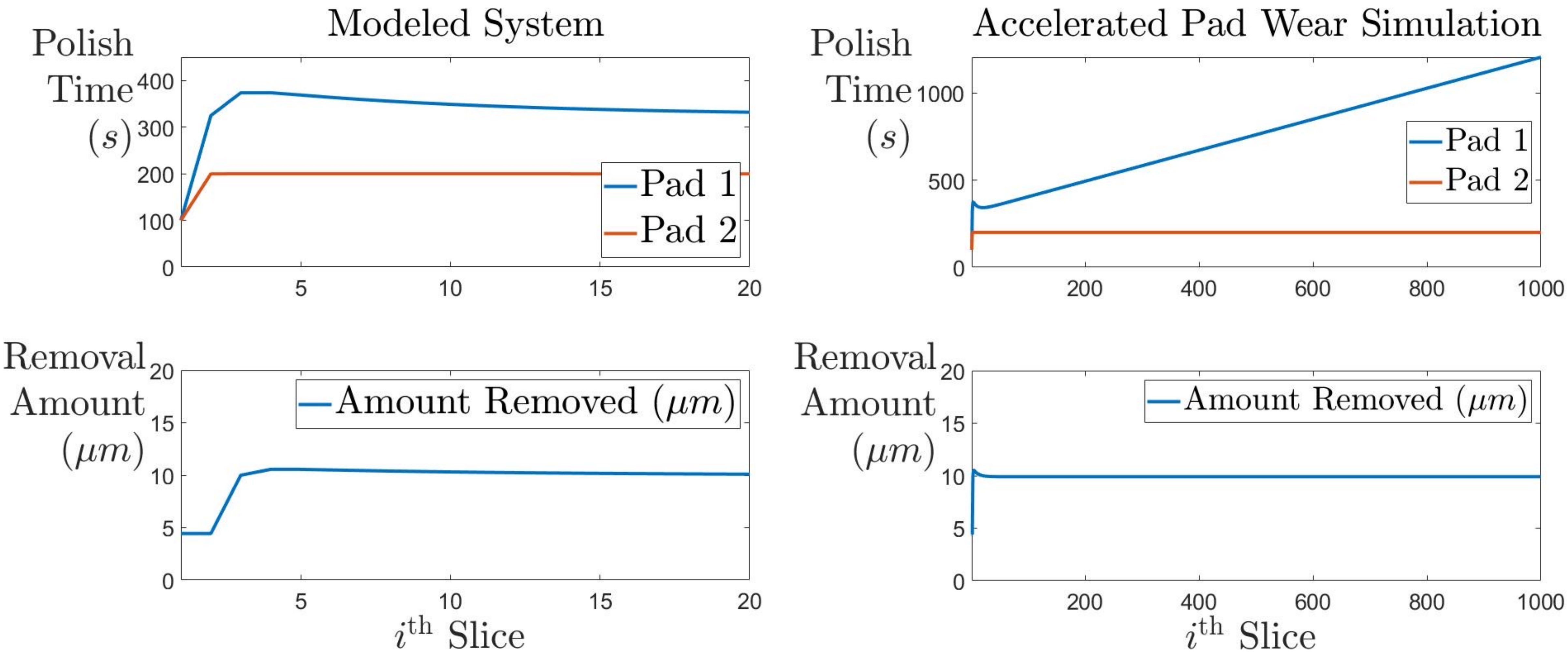
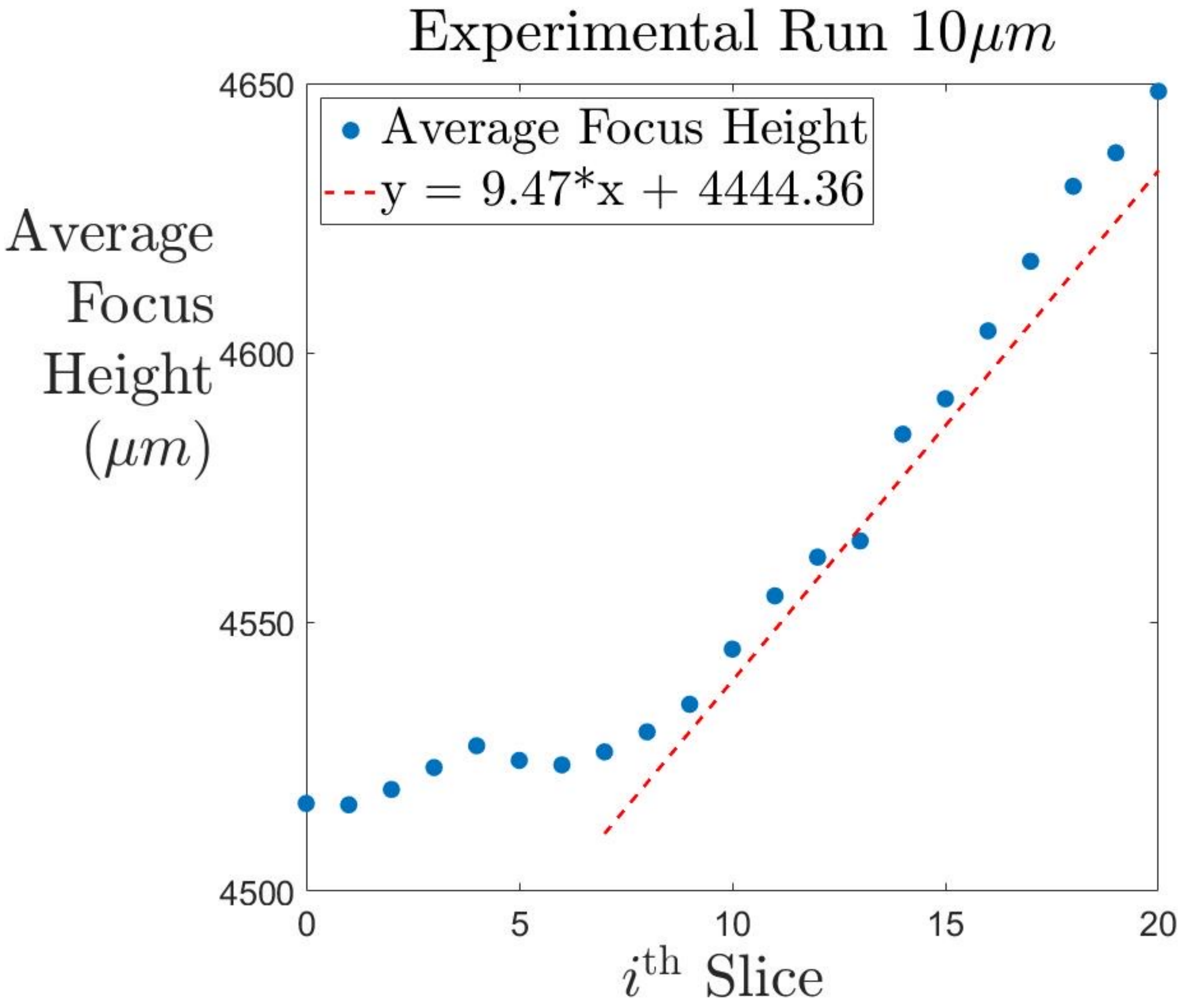


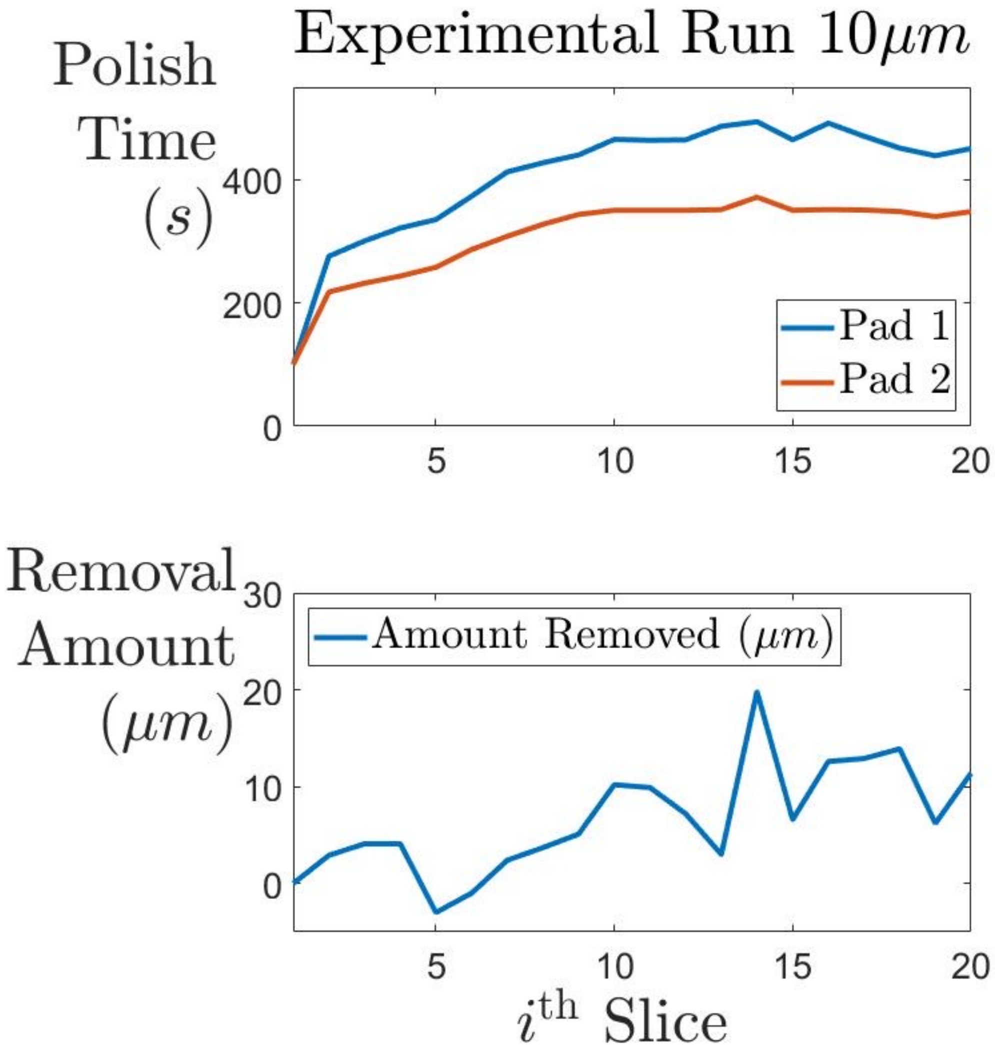


Simulation Results

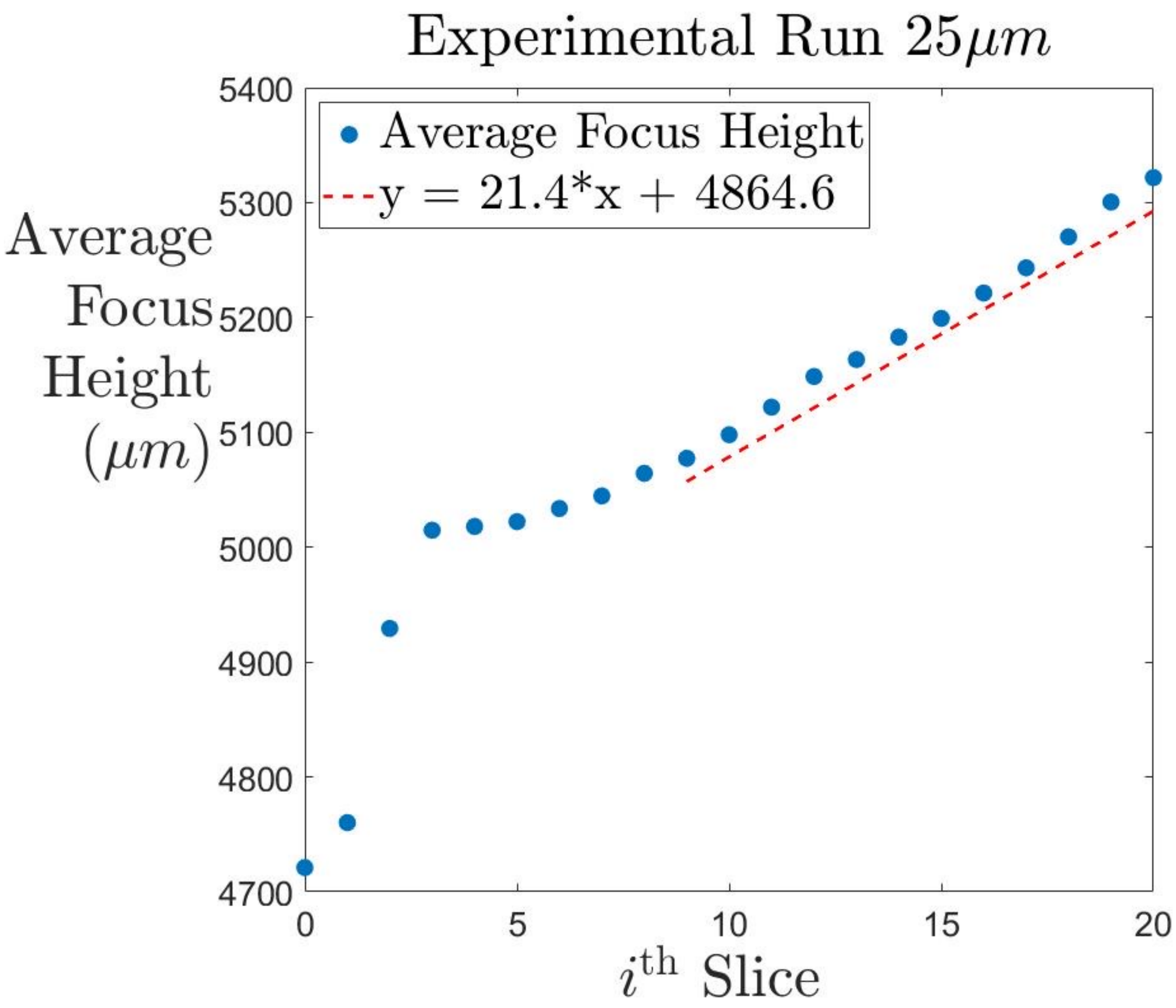


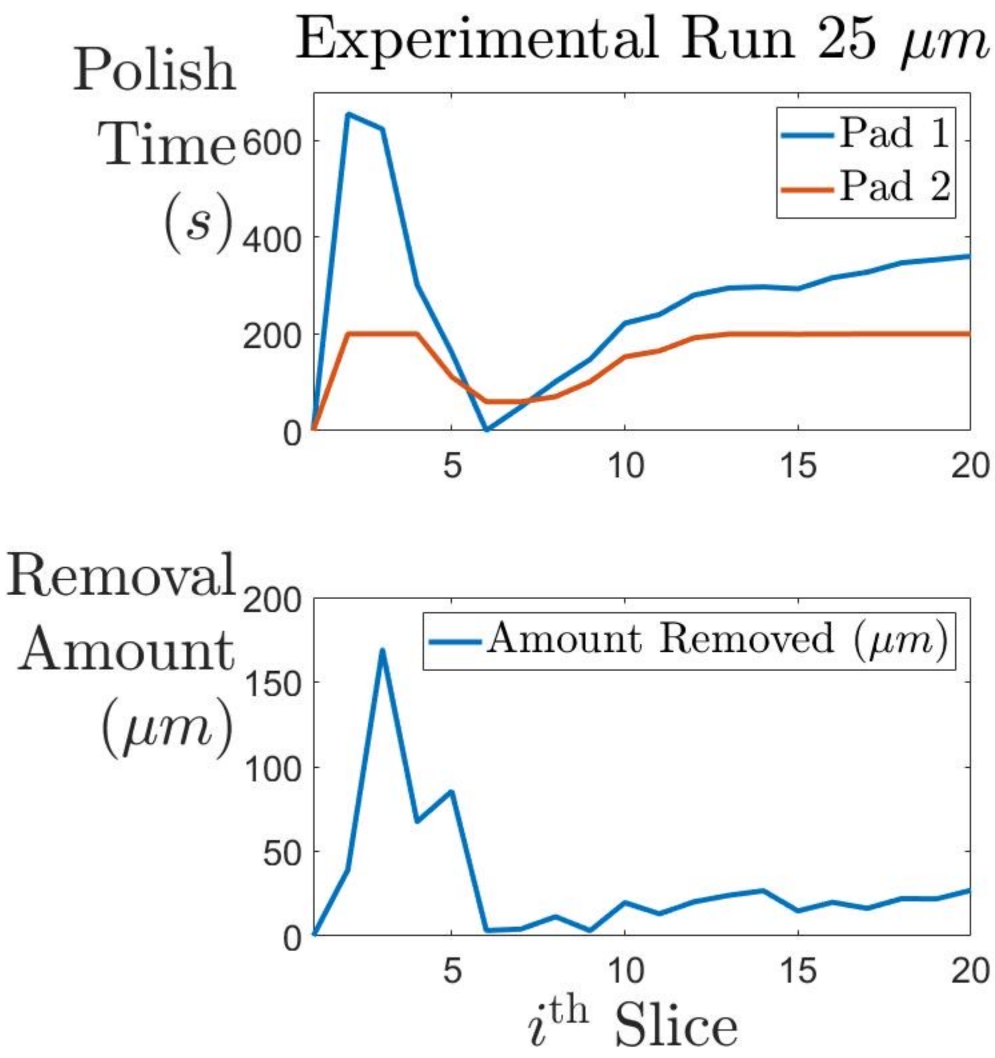
Physical System Results





Physical System Results





Conclusion

- Using an engineering controls approach, we have developed an experimentally accurate model estimate and system abstraction for a mathematical model of an automated mechanical serial-sectioning system

- Using iterative run-to-run control, we've developed and successfully demonstrated a means to transform an open-loop automated mechanical serial-sectioning system into a closed-loop operation that can iteratively revise inputs to produce an optimized experimental setup for a given criteria.

- Using historical data from a decade of experiments, an optimization algorithm was trained which, when implemented, was shown to converge to within 94%+/- 10% of a predetermined target removal rate within 10 iterations or fewer for both a previously executed and a never-before run experiment

Future Work

- Moving forward, we would like to examine the following:
  - Develop a mathematical criteria for image quality to operationalize it as an optimization criteria in this closed-loop approach
  - Expand our existing optimization framework to include immediately accessible experimental parameters such as polishing pad speed (i.e. RPM); polishing pad selection (i.e. cloth knap and/or grade); and polishing suspension (i.e. abrasive type and size)
  - Improve our model accuracy through methods such as a Gaussian Process Regression which should, in theory, also aid model efficiency

Questions

References

- Madison, J. D., Underwood, O. D., Poulter, G. A., & Huffman, E. M. (2017). Acquisition of real-time operation analytics for an automated serial sectioning system. *Integrating Materials and Manufacturing Innovation*, *6*(2), 135–146. https://doi.org/10.1007/s40192-017-0091-6

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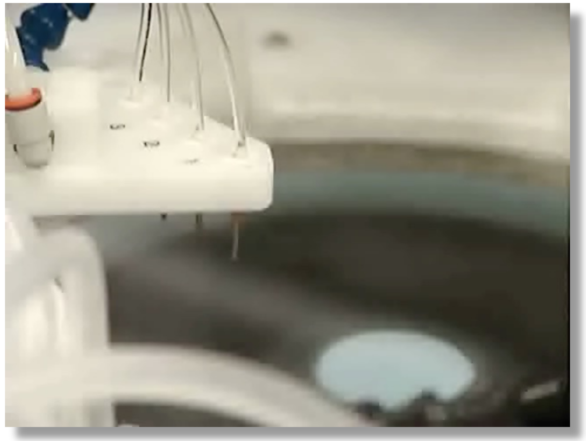
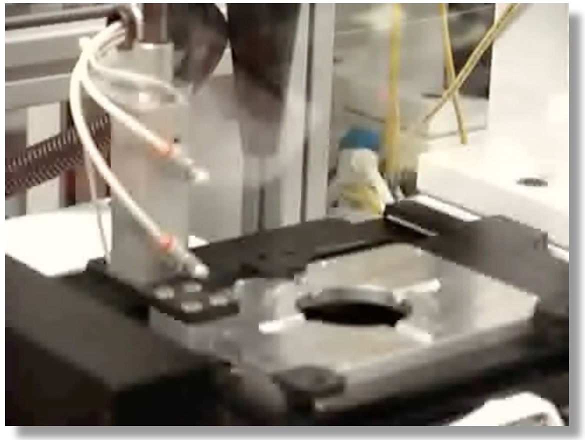
Platen Load



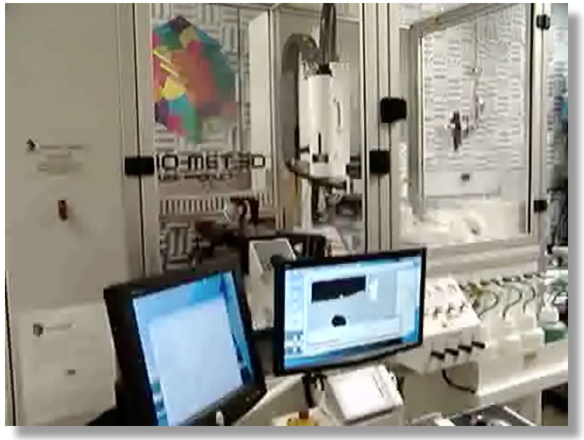
Sample Polish

Sample Rinse

Ultrasonic Bath & Air Dry

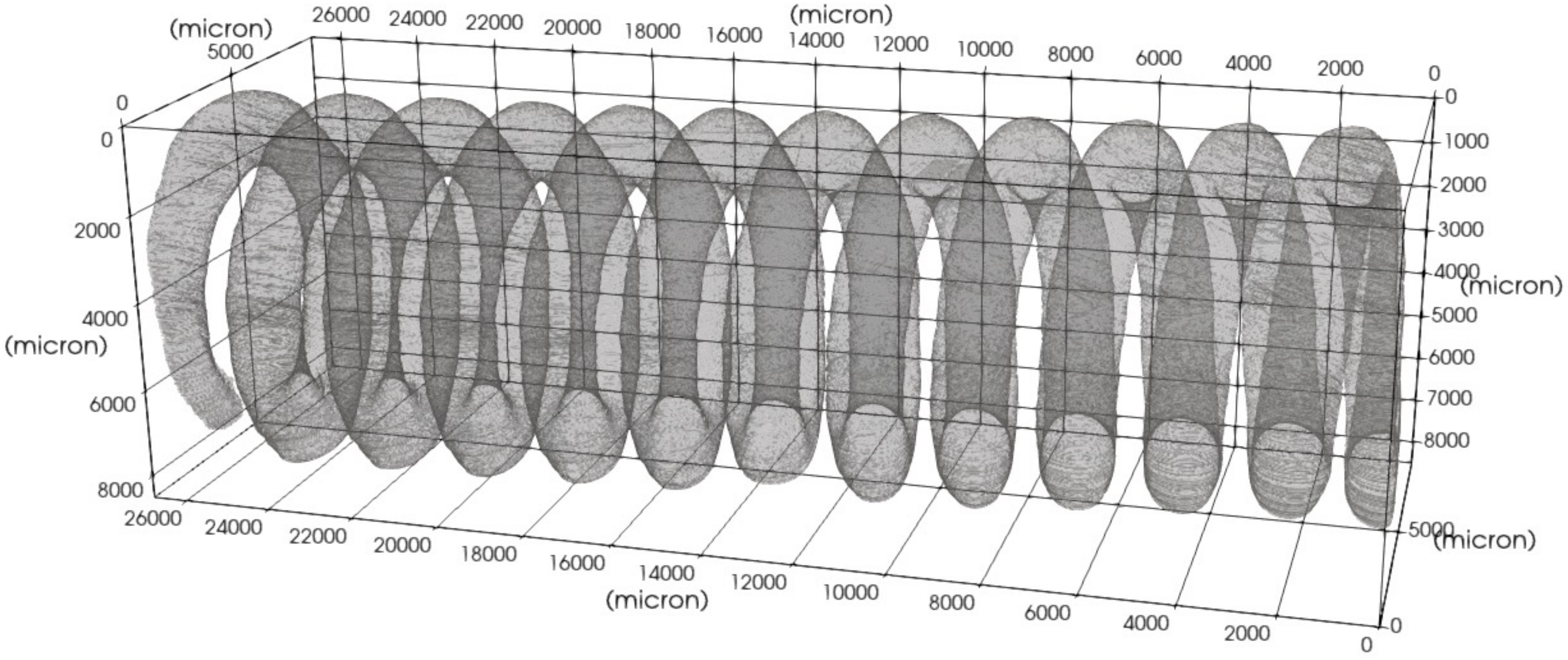


Microscope Load



Montage Imaging

3D Datasets


(micron)
5000
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0
2000
4000
(micron)
6000
8000
26000
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5000
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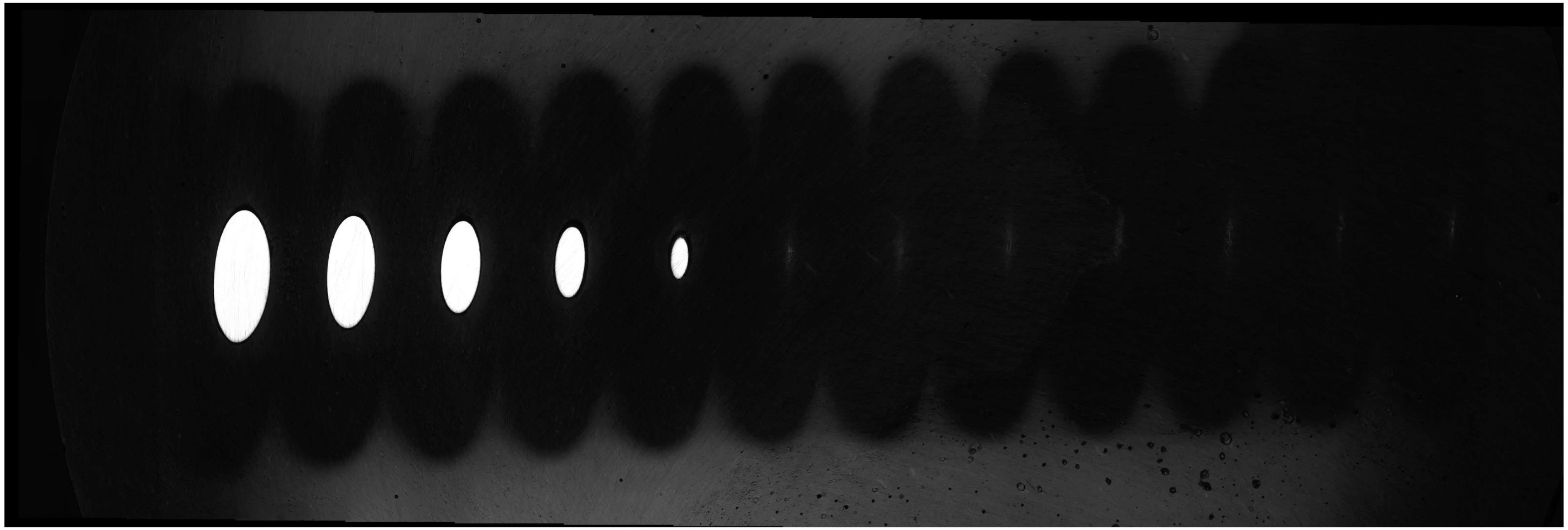
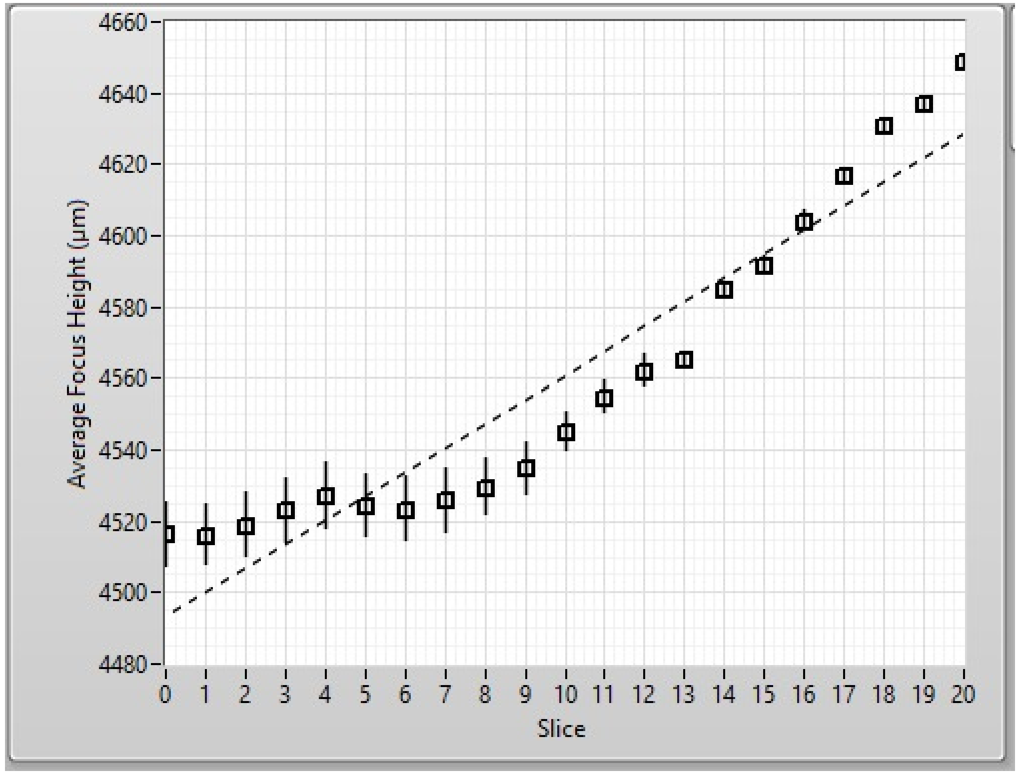
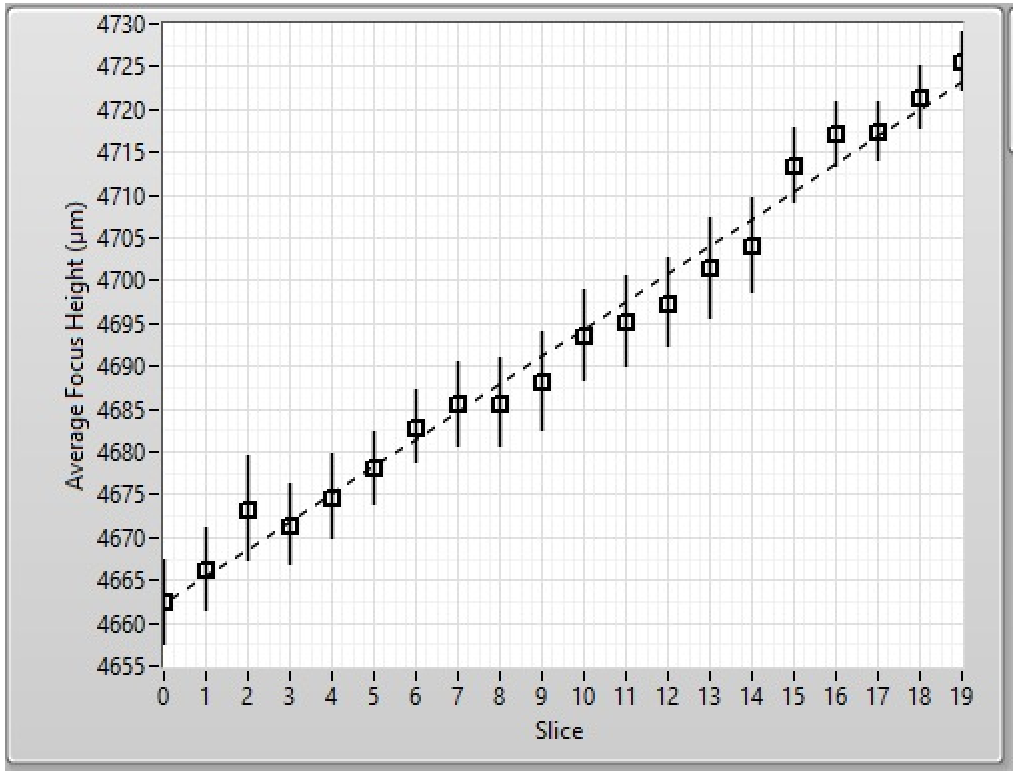
Motivation



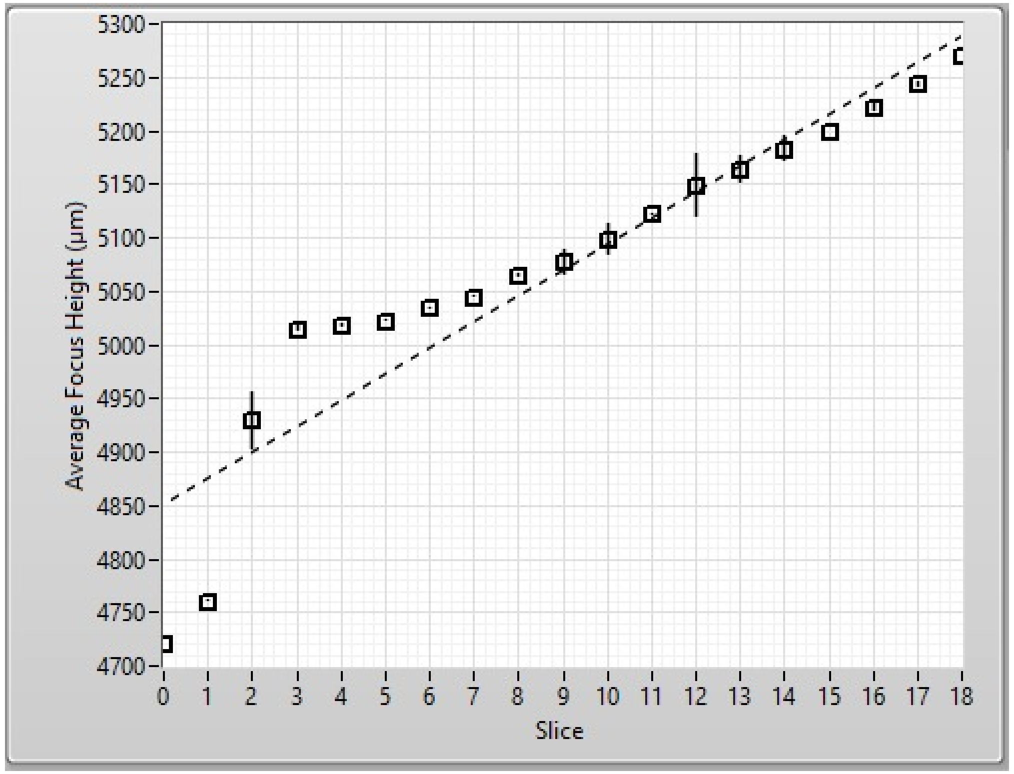
Physical System Results

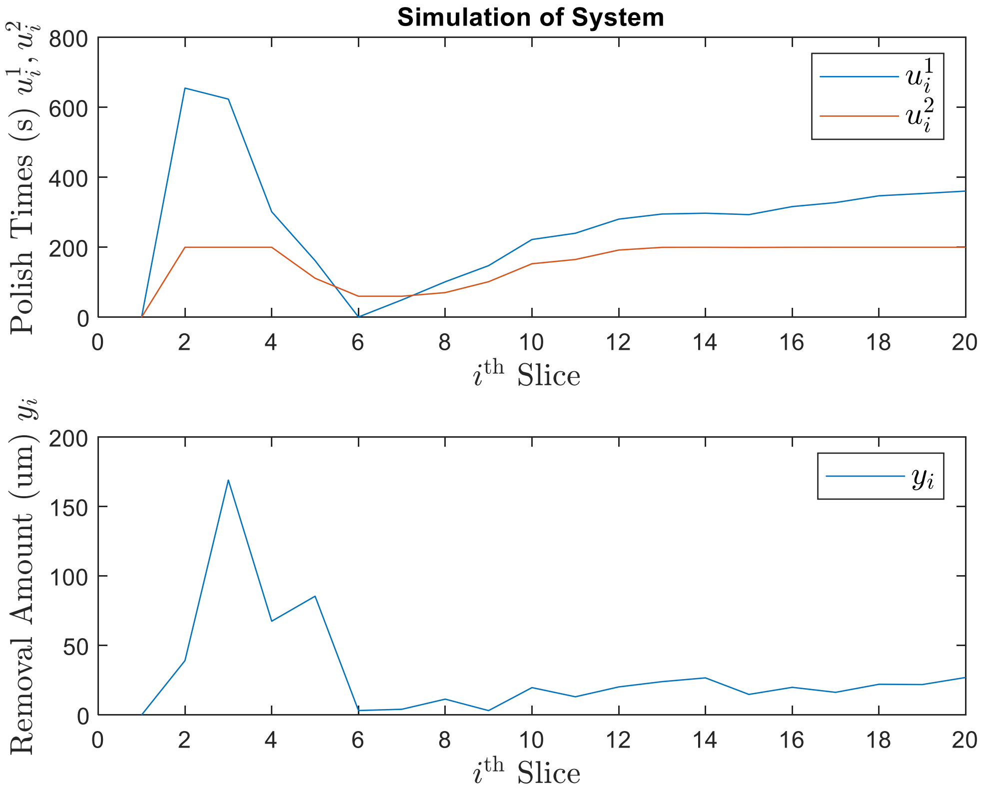




- Total 6.7 average removal, 9.47 after 6 slices. Target 10.
- Total 3.2 average removal. Target 5

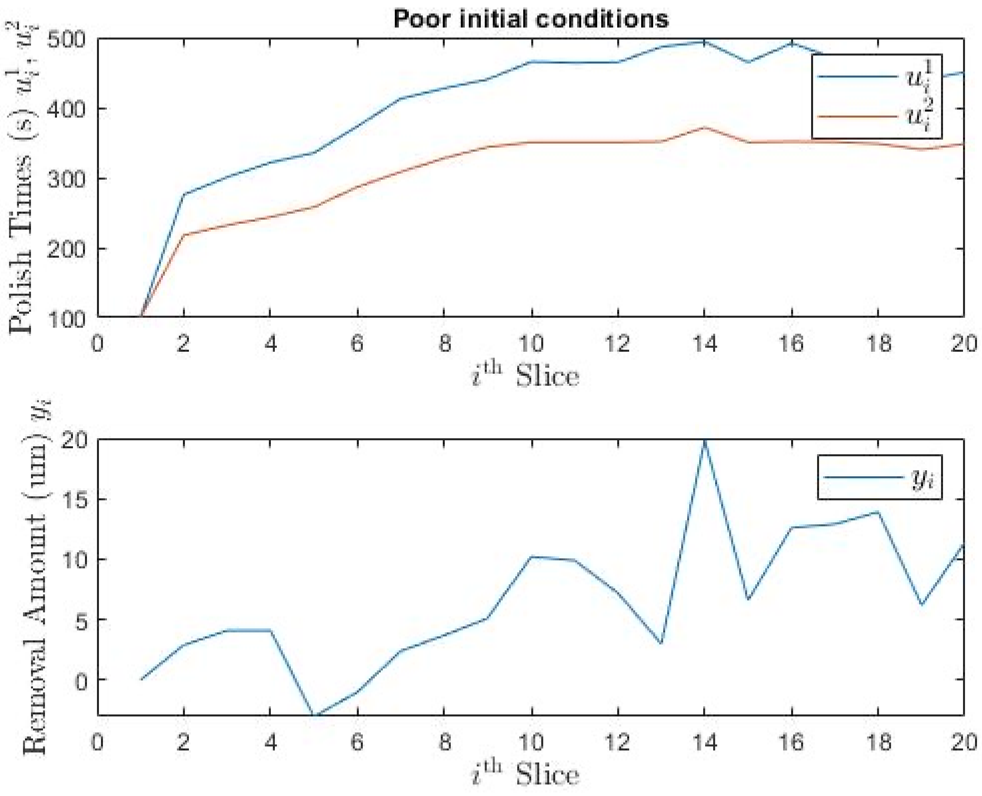
Physical System Results

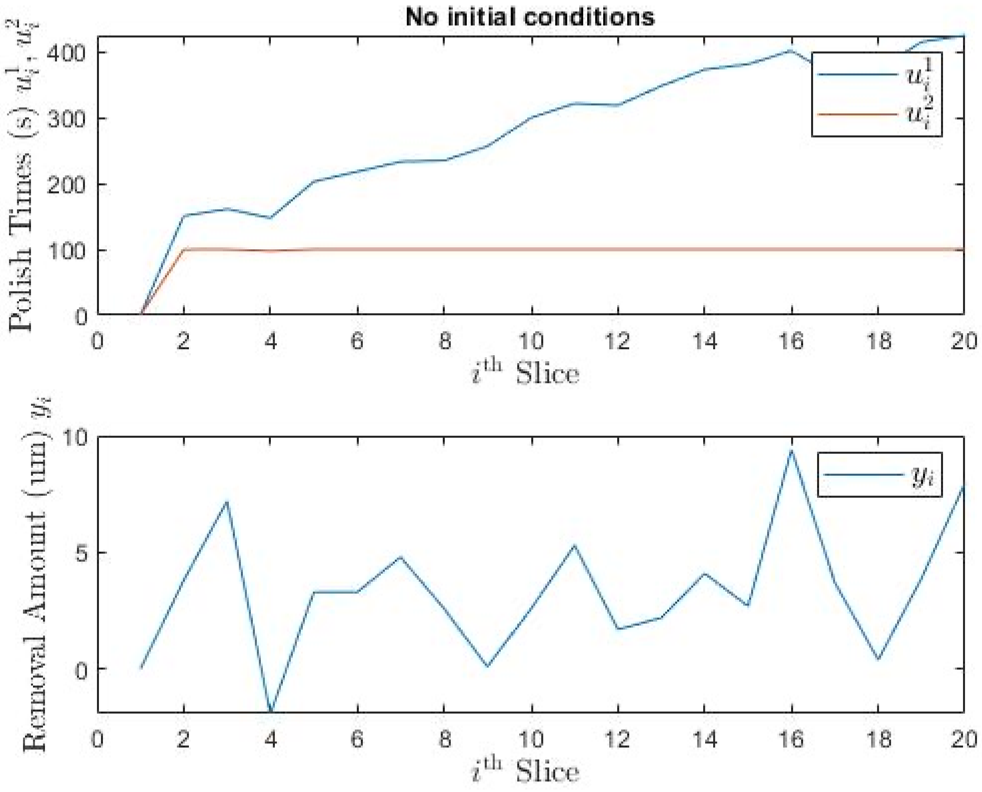




- Total 24.4 average removal.. Target 25.

Physical System Results





- Major points