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ROBUST DATA-DRIVEN RUN-TO-RUN CONTROL FOR AUTOMATED SERIAL SECTIONING

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ROBOMET.3D

Robo-Met.3D is a fully automated characterization technique for 3D investigations of microstructure using mechanical serial sectioning

- Serial sectioning is the removal of material layer-by-layer and then optical imaging
- RoboMet.3D provides 3D reconstructions of microstructure across volumes of cubic centimeters at resolutions of microns.

System Components

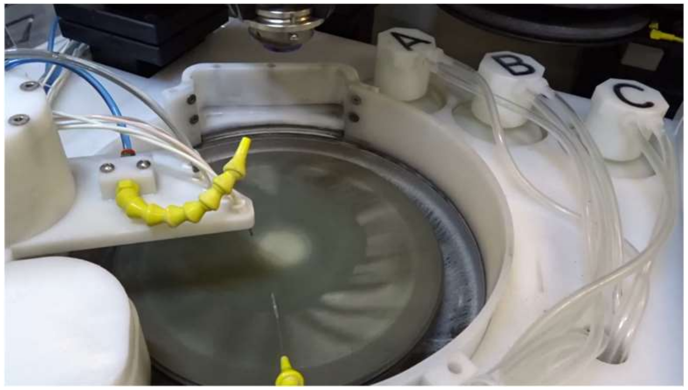
- Automated robotic polisher and interchangeable polishing pads
- Automated high resolution inverted Zeiss microscope with montage imaging
- Dual internal ultrasonic cleaning stations
- Three internal compact chemical etching stages
- External operator station for real-time observation of data collection

Benefits

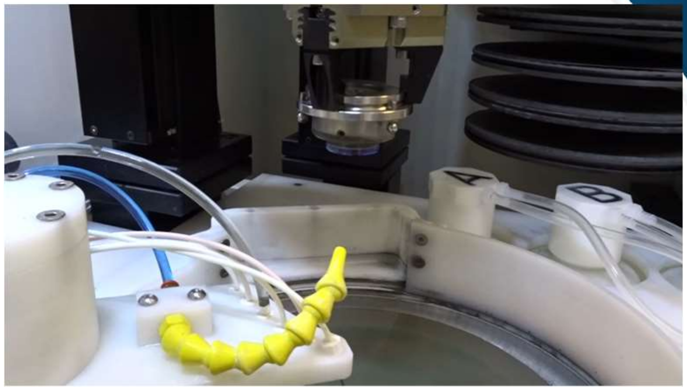
- Sectioning rates up to 10 times the baseline manual process
- Elimination of variability caused by human handling
- Precise repeatability and command over imaging
- Demonstrated repeatable sectioning thicknesses from 0.2 – 10 mm per slice
- Documented slice rates of up to 20 slices per hour
- Applicable to high and low strength metals, thermal spray & geology samples
- Can run continuously 24/6

ROBOMET.3D

Platen Load

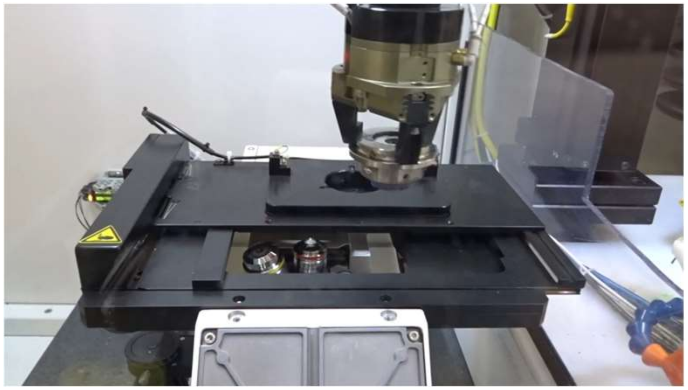


Sample Polish



Sample Rinse

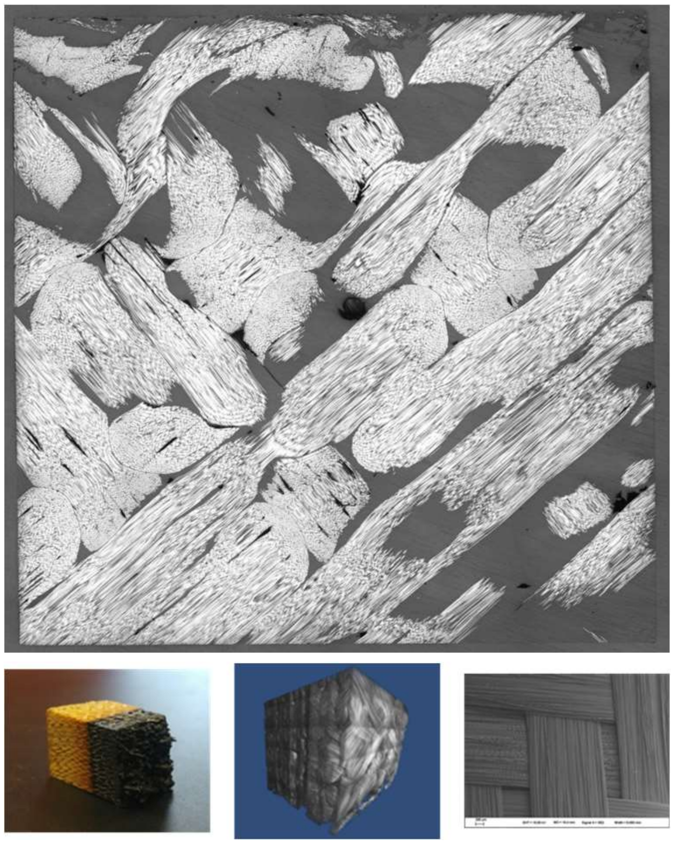
Ultrasonic Bath



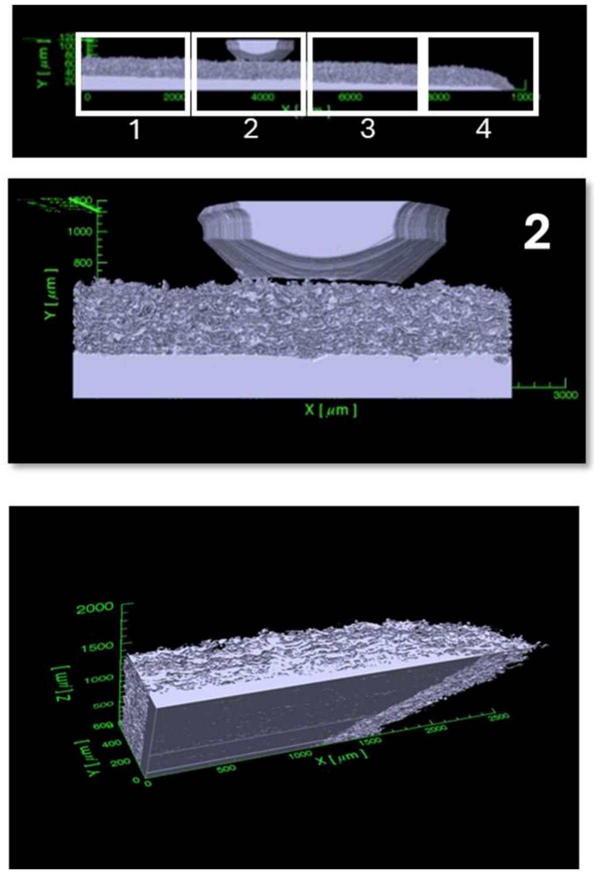
Microscope Load

Montage Imaging

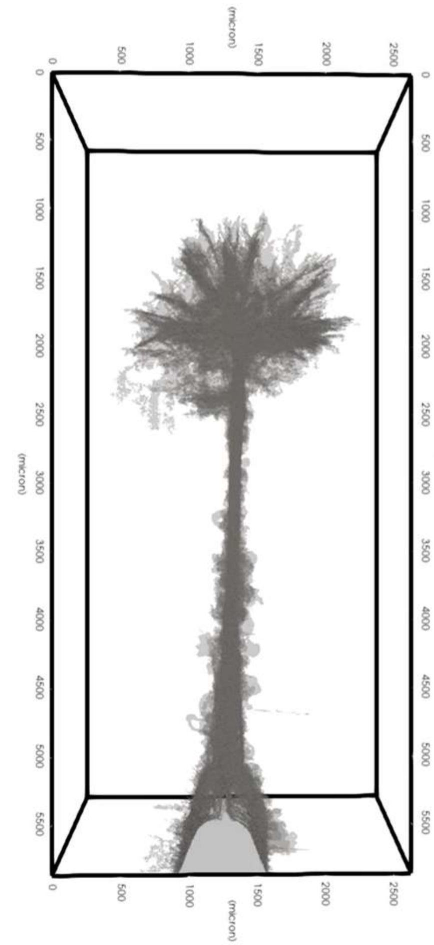
MECHANICAL SERIAL SECTIONING



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

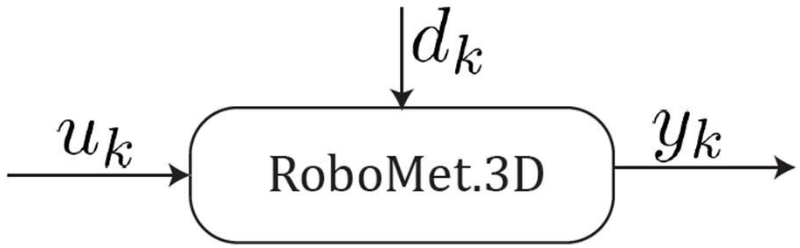


Subsurface damage in thermal spray coatings [3]



Stress Corrosion Crack in Steel

LIMITATIONS OF OPEN-LOOP CONTROL

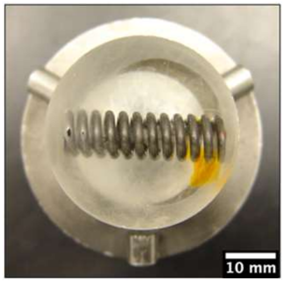


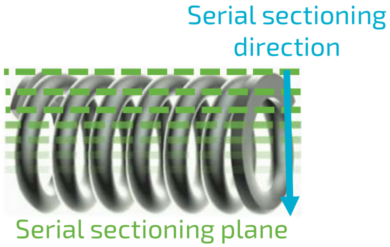
u_k = **input recipe,** y_k = **measured material removal,** d_k = **unmeasured disturbances**

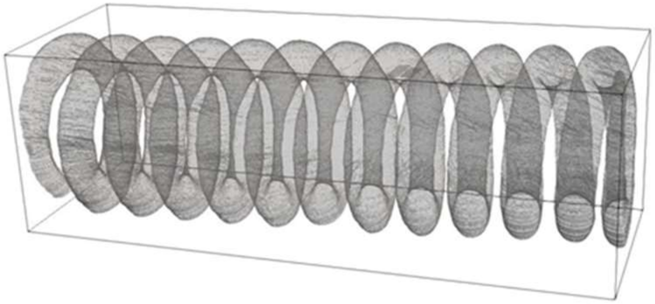
- Material removal rates are inconsistent from component to component requiring a 'calibration phase'.
  - A series of test runs to identify the appropriate duration for each pad.
  - Challenge: multiple ways to achieve a target slice thickness with uncertainty of the correlation between pad times and removal rates.
- Recipe is typically fixed after the calibration phase.
- Lack of real-time feedback and adjustment, leading to inconsistencies in the material removal process

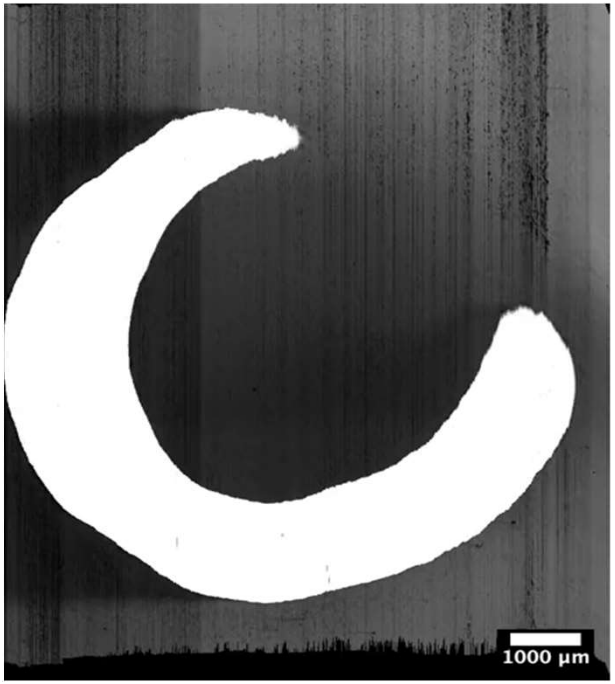
MOTIVATION

Inconsistent slicing thickness resulting in a distorted representation of the spring.

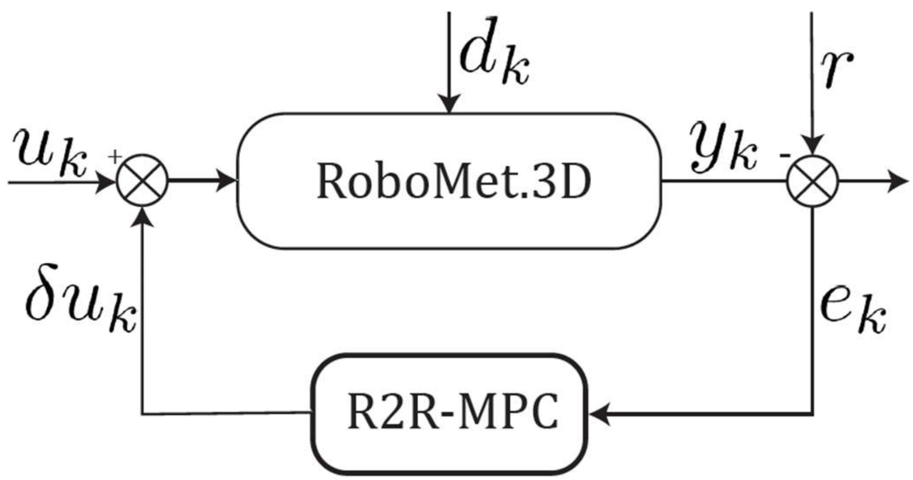








RUN-TO-RUN (R2R) CONTROL



- A closed-loop R2R framework provides a feedback mechanism for adjusting the recipe u_k based on the slice error.

$$e_k = r_k - y_k$$

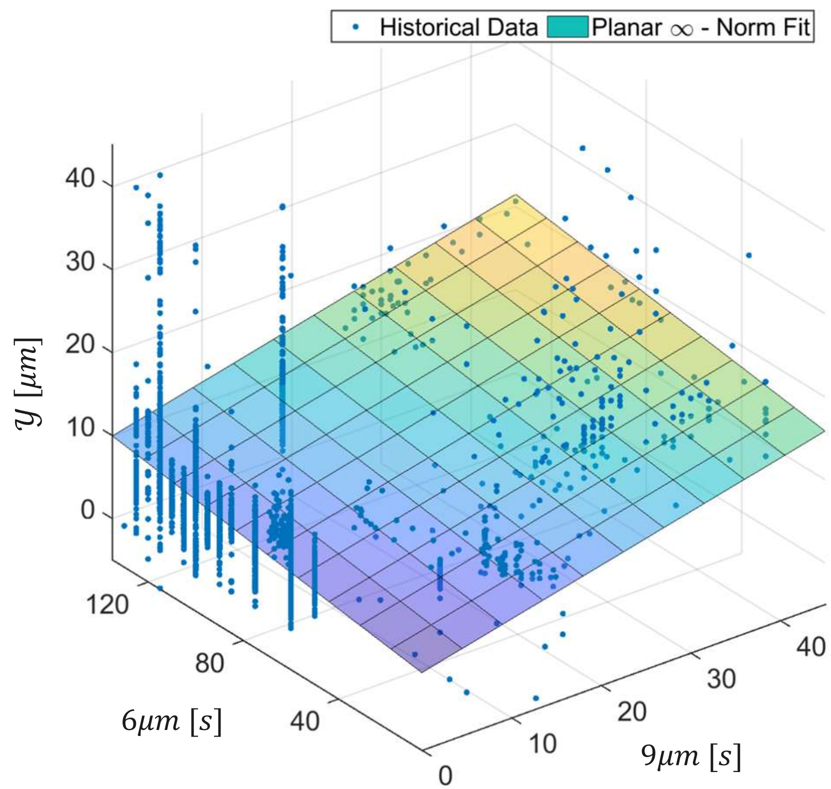
- **Goal:** Compute a sequence of physically implementable recipes u_k such that the actual material removed y_k tracks the target removal r_k despite unmeasured disturbances d_k.

REMOVAL FUNCTION

- Removal function is unknown, making is difficult to predict the outcome of a recipe.

$$y_k = f(u_k, d_k)$$

- Unmeasured disturbances d_k can affect the removal process, introducing time-varying uncertainty that is difficult to compensate for in real-time.
- There are multiple input combinations that can achieve the same removal, but not all are equally efficient, robust, or consistent with the physical system constraints.



ONE-STEP CONSTRAINED OPTIMAL CONTROL PROBLEM

- We find the optimal recipe by solving the optimization problem for the incremental input δu_k^*.
- Optimization problem seeks to minimize the worst case error of the next slice subject to a linear differential inclusion incorporating the uncertainty parameter, b.

Variable	Real World Value
r	Target Removal Amount
δu_k	Change in System Input
u_k	Current System Input
u_{k+1}	Subsequent System Input
e_k	Error of Current Slice
e_{k+1}	Error of Subsequent Slice
b_j	Uncertainty Parameter

Optimization Problem

$$\delta u_k^* = \arg\min e_{k+1}$$

$$\text{s.t. } e_{k+1} \geq e_k - b_j^T \delta u_k, j = 1, \dots, M$$

$$u_k + \delta u_k \in \mathcal{U}$$

Incremental Input

$$u_{k+1}^* = u_k + \delta u_k^*$$

Error

$$e_k = r_k - y_k = r_k - f(u_k, d_k)$$

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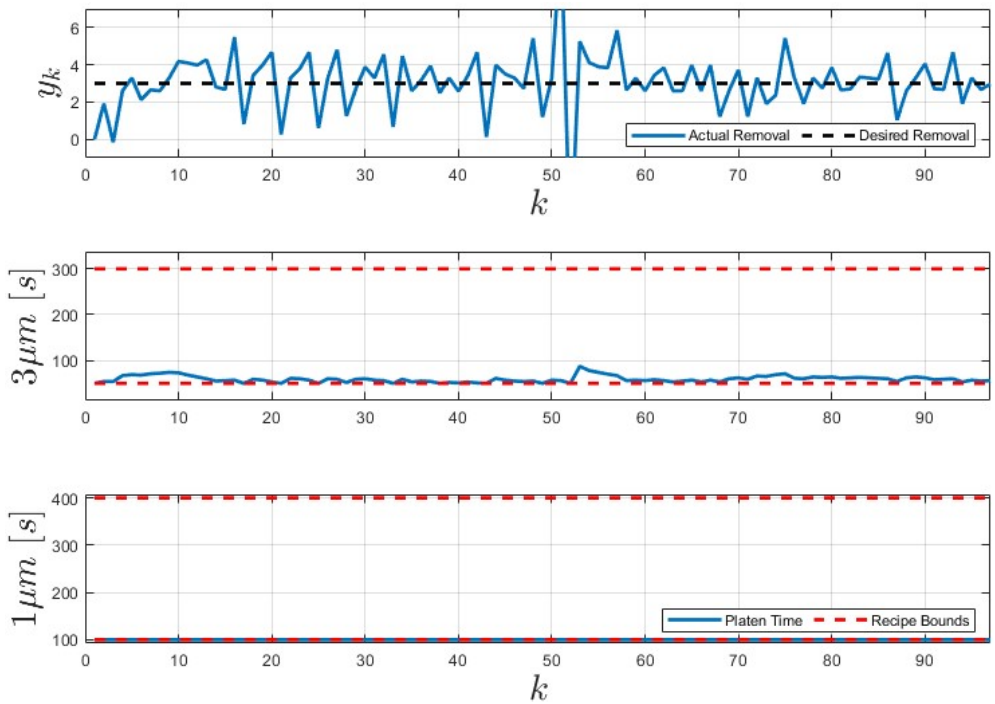
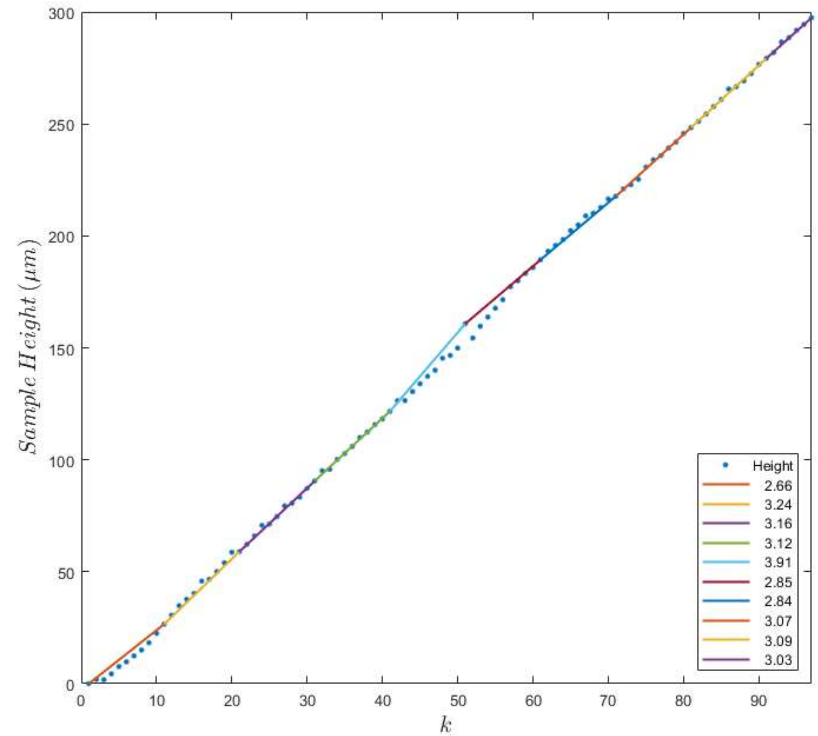
EXPERIMENTAL DATA – 2-PLATEN RECIPES

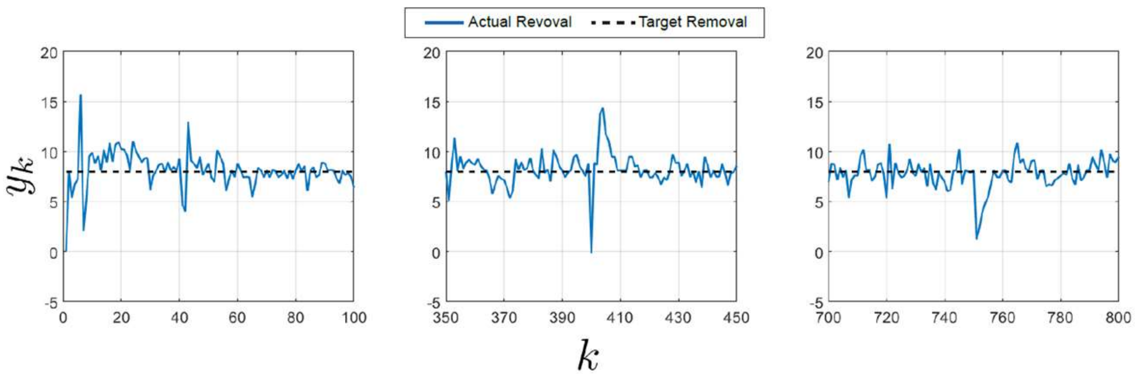


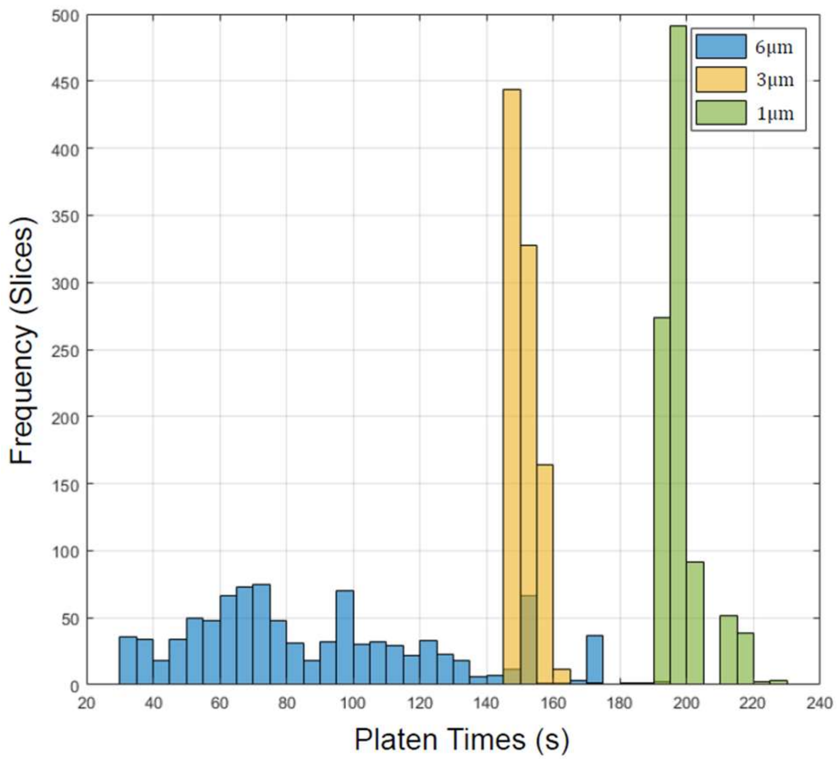


Target Removal: $r = 3\mu m$

- The actual removal experiences some variability on a local scale, but demonstrates consistency on a global scale

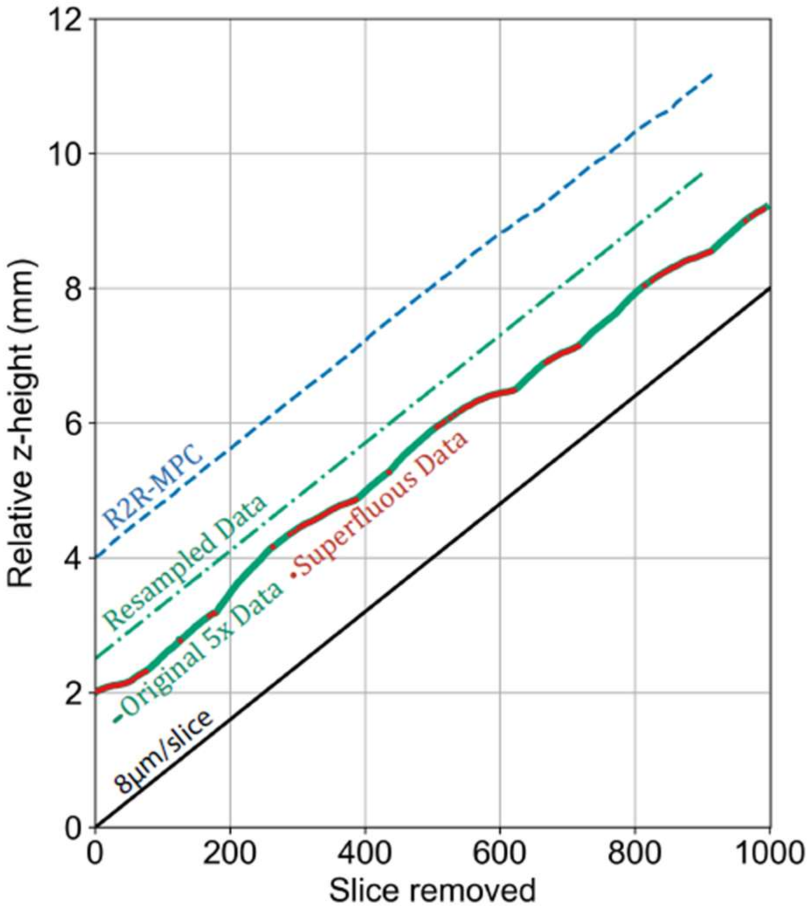
EXPERIMENTAL DATA – 4-PLATEN RECIPES





- Target Removal: $r = 8\mu m$
- Controller reached the target removal within 25 slices.
- The trajectory of the actual removal track the target removal over 800 slices despite evidence of excessive noise.
- The $6\mu m$ platen experiences the most variance in platen time.

COMPARISON TO HISTORICAL PERFORMANCE



Open-loop Control

- Operator had to make manual adjustments to the recipe.
- Instances of over sampling resulted in the removal of nearly 100 slices of superfluous data.

Closed-loop Control with R2R-MPC

- Consistent removal over 900 slices with minor deviation from the target removal.

CONCLUSIONS

1. The R2R-MPC controller automates recipe inputs, rejects disturbances, and adjust to changing material, reducing the need for constant operator supervision.
2. The controller minimizes post-processing time by significantly decreasing the amount of data discarded during post-processing, leading to more accurate and consistent data collection for 3D reconstruction.
3. Overall, the R2R-MPC controller has proven to be a robust solution for improving the consistency and reliability of the RoboMet.3D system.
4. The implementation offers substantial time and cost savings while ensuring high-quality data.

QUESTIONS

INCREMENTAL ERROR DYNAMICS

$$\delta u_k = u_{k+1} - u_k$$

$$e_k = r_k - y_k = r_k - f(u_k, d_k)$$

$$e_{k+1} = r_{k+1} - f(u_{k+1}, d_{k+1})$$

$$\approx r_{k+1} - y_k - \nabla_u f(u_k, d_k)\delta u + \nabla_d f(u_k, d_k)\delta d$$

$$e_{k+1} \approx e_k - \nabla_u f(u_k, d_k)^T \delta u_k$$

- Integral-action is the classical approach in MPC for achieving the reference tracking and disturbance rejection control objectives
- A first-order Taylor approximation is used to describe the error in its incremental form to achieve integral action.
- We assume the disturbance is constant $d_{k+1} = d_k$ for simplification and because it is unmeasurable.
- The incremental input will be computed by our controller.

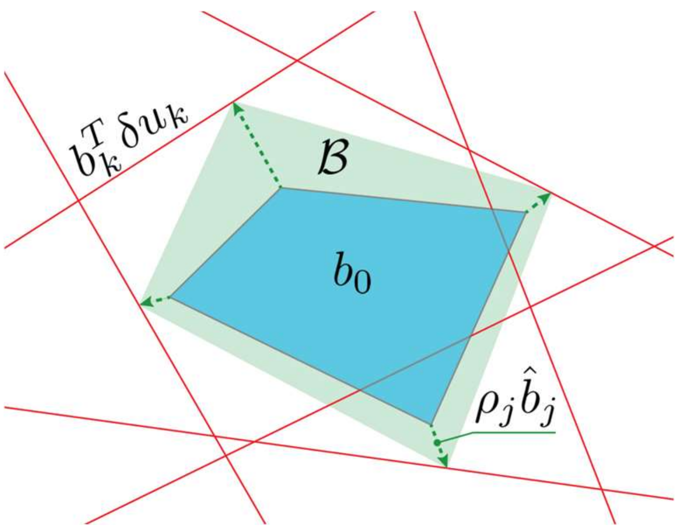
UNCERTAINTY BOUNDS

Linear Differential Inclusion:

$$e_{k+1} \in \mathcal{E}(e_k, \delta u_k) = \left\{ e_k + b^T \delta u_k \in \mathbb{R} : b \in \mathcal{B} \right\}$$

Uncertainty Set:

$$\mathcal{B} = \{b_0\} \oplus \text{conv}\left\{ \rho_1 \hat{b}_1, \ldots, \rho_M \hat{b}_M \right\}$$



- The gradient $\nabla_u f$ in the approximate incremental error model is unknown. We model as a linear differential inclusion.
- Uncertainty parameter $b \in \mathcal{B}$ captures the unknown gradient $\nabla_u f \approx b$ as well as the approximation error.
- Using thousands of hours of historical operational data:
  - The 'center' $b_0$is computed as an optimal infinity norm of the date
  - An algorithm is then used for each data point to determine which expansion direction $\hat{b}_j$ requires the least expansion ρ_j to cover that data point $\delta y_i = \left(b_0 + \rho_j \hat{b}_j\right)^{\mathrm{T}} \delta u_i$

ONE-STEP CONSTRAINED OPTIMAL CONTROL PROBLEM

$$\begin{aligned} \delta u_k = \arg\min \quad & e_{k+1} \\ \text{s.t.} \quad & e_{k+1} \geq e_k - b_j^T \delta u, j = 1, \ldots, M \\ & u_k + \delta u_k \in \mathcal{U} \end{aligned}$$

$$u_{k+1}^{\star} = u_k + \delta u^{\star}$$

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