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MELT POOL DEPTH PREDICTION IN DIRECTED ENERGY DEPOSITION SINGLE-TRACK PRINTS USING POINT CLOUD ANALYSIS

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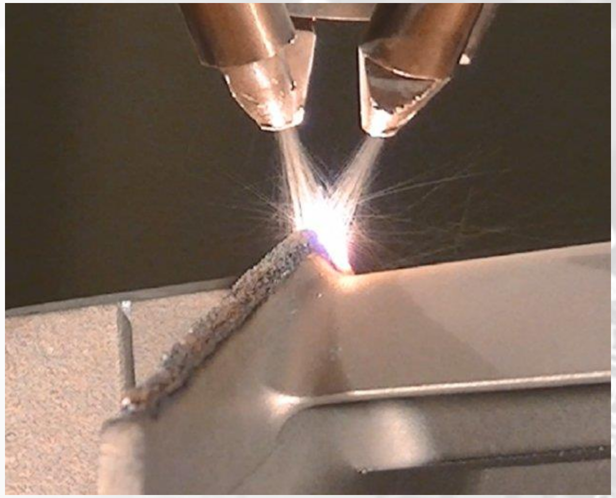
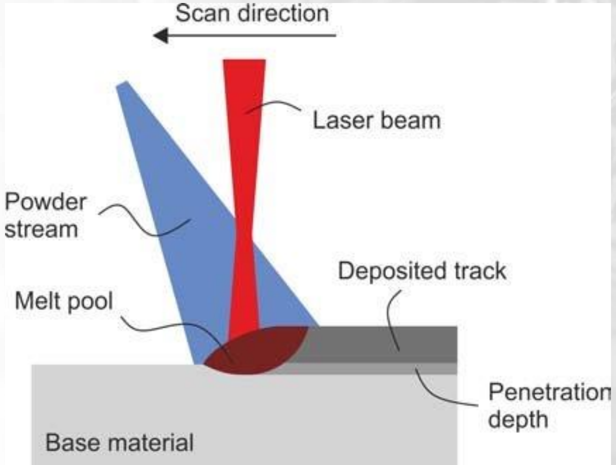
Introduction

- ***Additive Manufacturing (AM)***
  - Computer-controlled manufacturing processes creating complex 3D objects layer-by-layer.
- ***Directed Energy Deposition (DED)***
  - **Process**: A metal AM process using a high-energy laser beam to melt and deposit powders, forming parts.
- ***Complex Physics***
  - **Interactions**: Involves heat transfer, fluid dynamics, and material properties.
  - **Importance**: Crucial for optimizing process parameters and part quality.
- ***Growing Interest in Melt Pool Features***
  - **Significance**: The melt pool directly influences the microstructure and properties of the part.
  - **Focus**: Increasing efforts on monitoring and controlling melt pool characteristics to improve stability and performance.

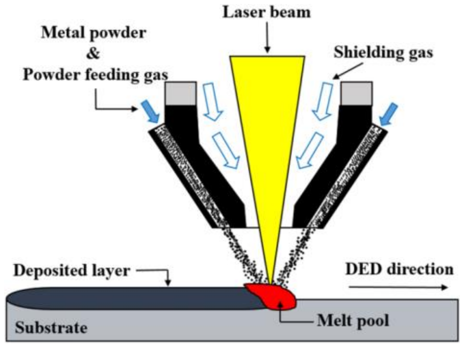


Khanzadeh et al. (2019)

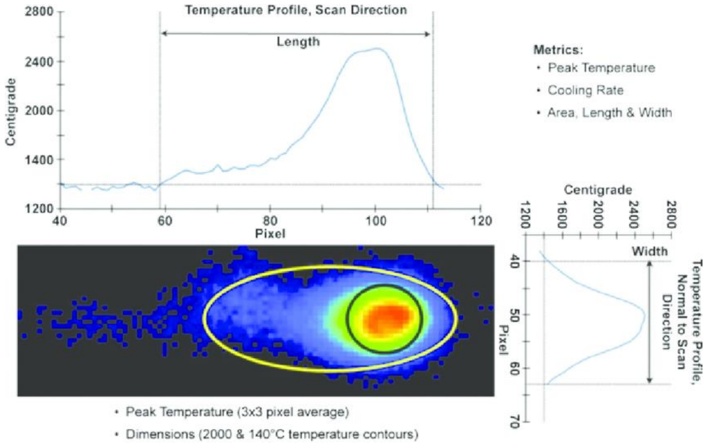


Eisenbarth et al. (2020)

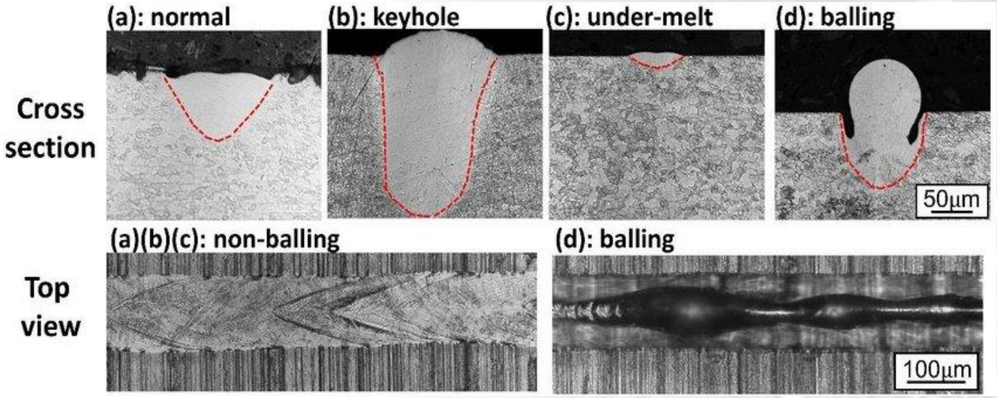
What is a Melt Pool? Why is it important to study?



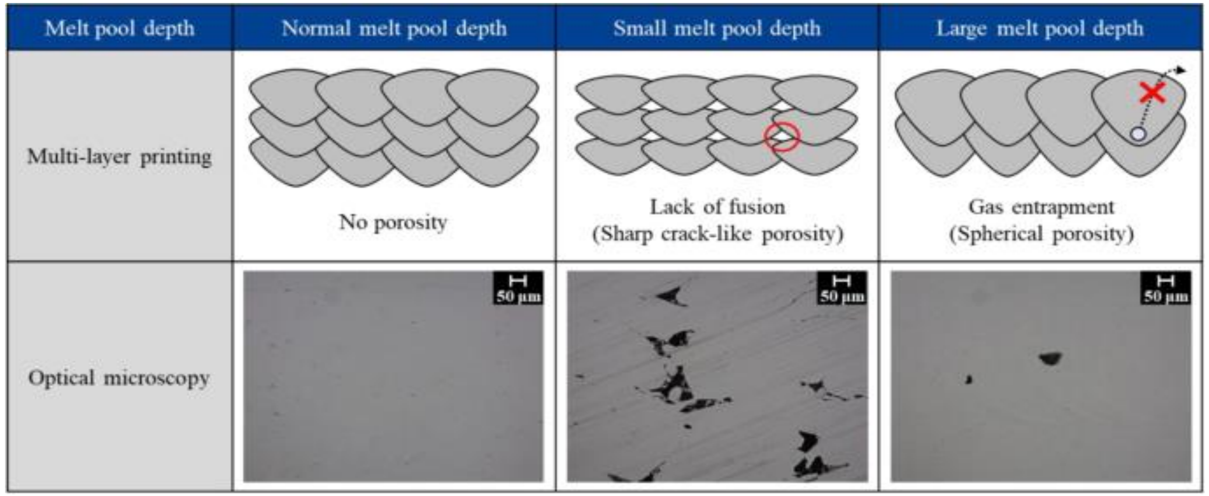
Lim et al. (2021)



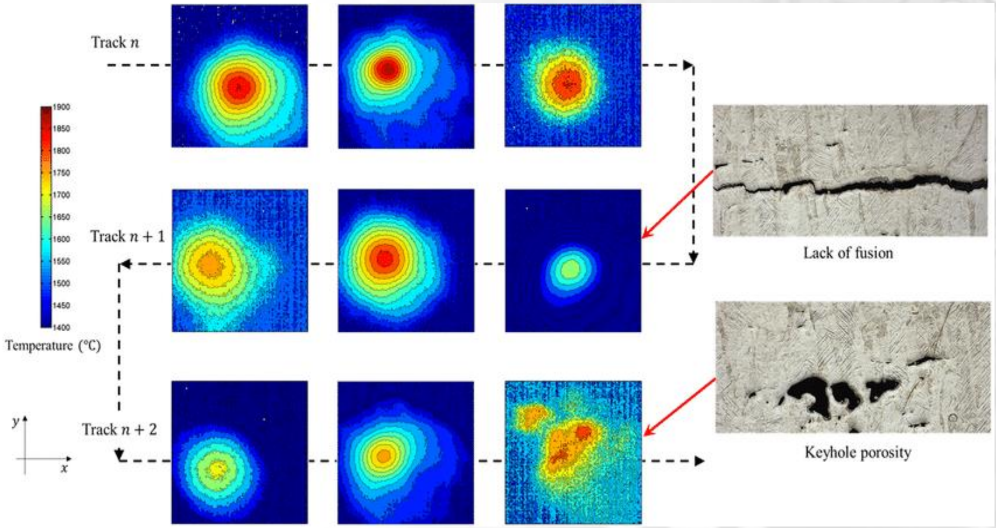
Peralta et al. (2016)



Yining et al. (2020)



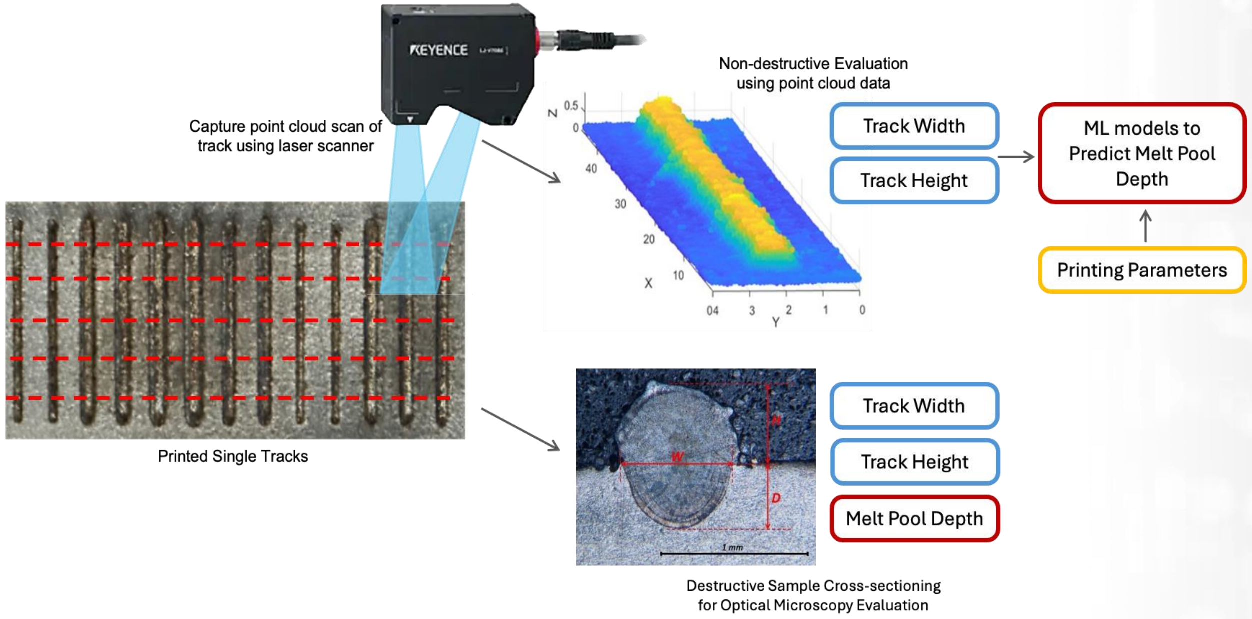
Jeon et al. (2023)



Khanzadeh et al. (2017)

Background and Motivation

- Melt pool depth is crucial in metal AM; however, it is not visible during the printing process.
- Traditional methods for evaluating the melt pool size are time-consuming, costly, and often destructive.
- We propose a novel solution to predict the melt pool depth in DED AM process using point cloud data from a laser scanner, integrated with machine learning (ML) techniques.
- Our method automates the point cloud data processing step, eliminating the need for manual intervention and enabling potential real-time, data-driven insights.

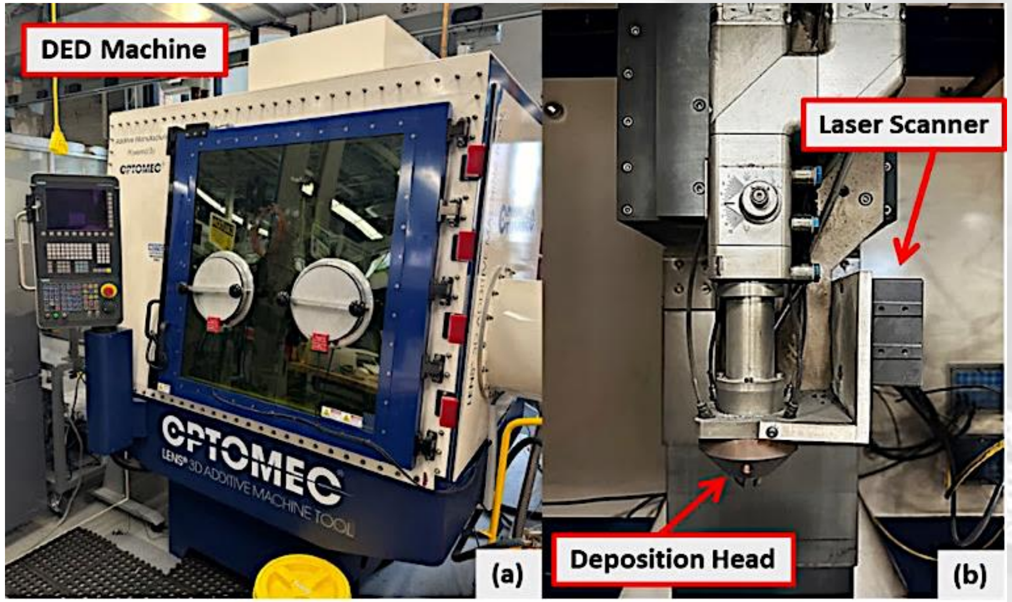


Experimental Studies

- As shown in Table 1, single-layer tracks (SS316L) with varying **laser power** (W), **scan speed** (mm/min) and **powder feed rate** (rpm), covering the three regimes ~ **conduction**, **transition**, and **keyhole** were printed and analyzed.
- All samples were fabricated on an Optomec Lens MTS 500 (**DED Machine**).
- The track width, height, and melt pool depth were:
  - Observed using **optical microscope** (OM) for validation studies
  - Calculated from the **point cloud data** scans captured using a high-speed 3D laser scanner (KEYENCE LJ-7000 Series) as shown in the next slide.

Table 1: Process parameters employed in this study

	Low	High
Laser Power (W)	200	500
Scanning Speed (mm/min)	10	1000
Powder Feed Rate (g/min)	2.7	20.1

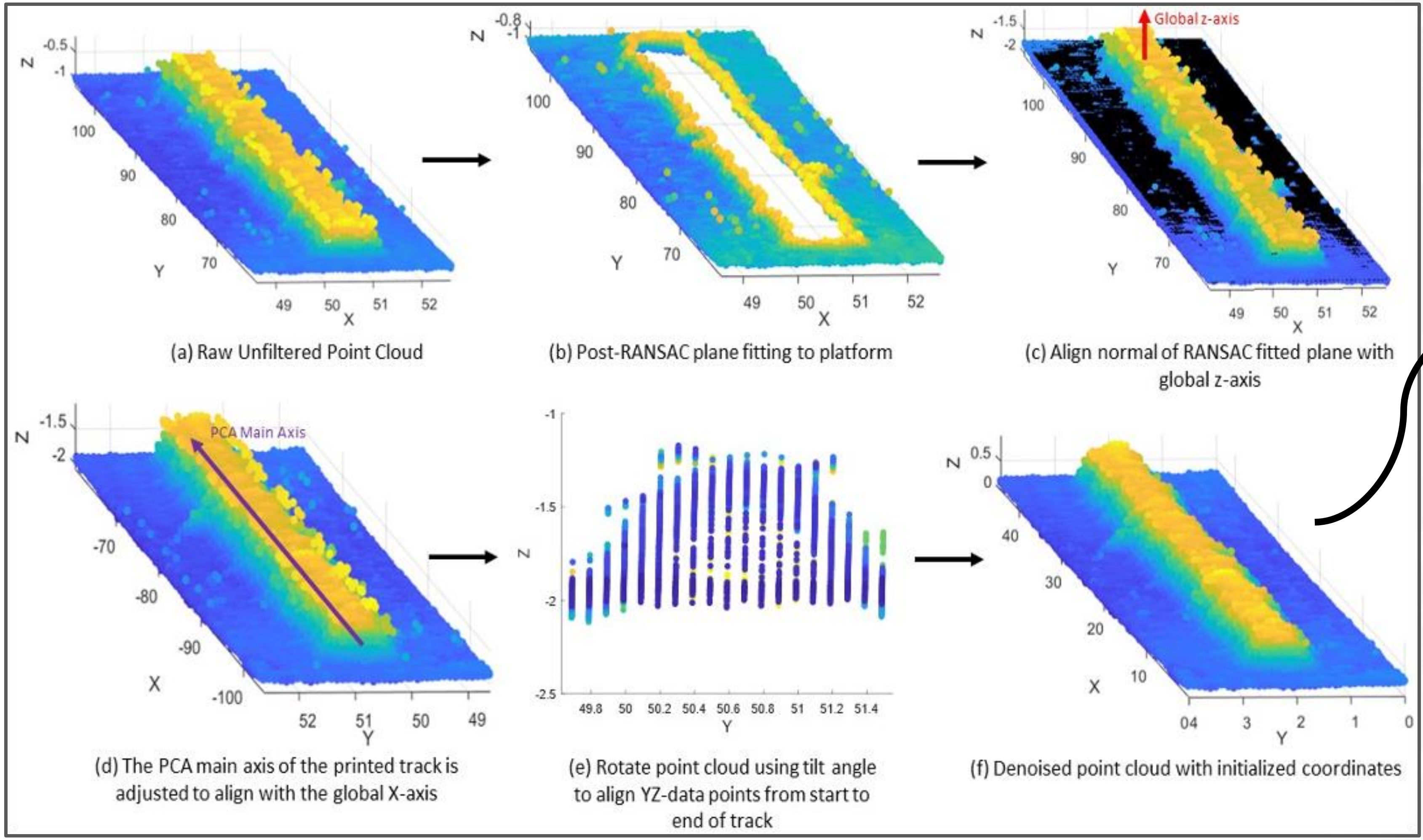


The experimental setup (a) DED machine (b) Inside view with deposition head and mounted laser scanner

(a) Conduction (b) Transition (c) Keyhole

Example cross-sections of single tracks, illustrating the three different regimes

Single Track Print's Point Cloud Data Denoising and Processing



(a) Raw Unfiltered Point Cloud

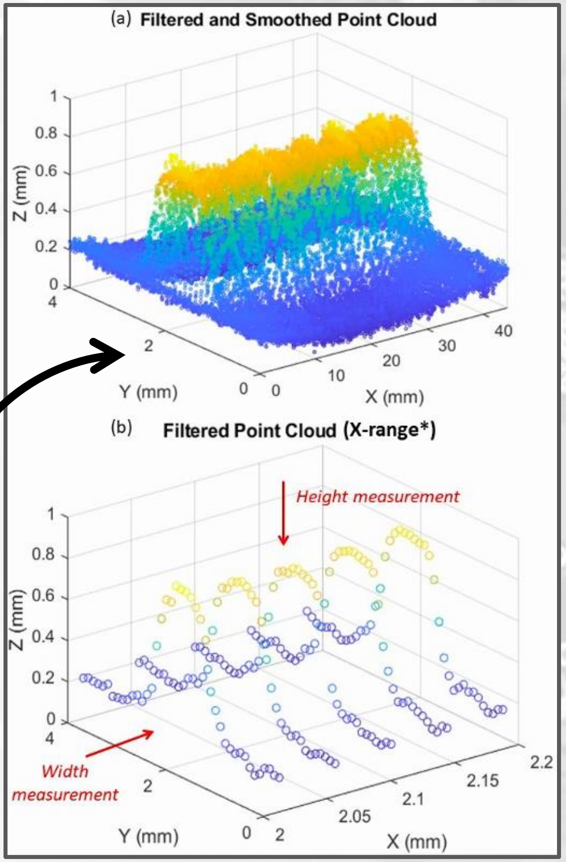
(b) Post-RANSAC plane fitting to platform

(c) Align normal of RANSAC fitted plane with global z-axis

(d) The PCA main axis of the printed track is adjusted to align with the global X-axis

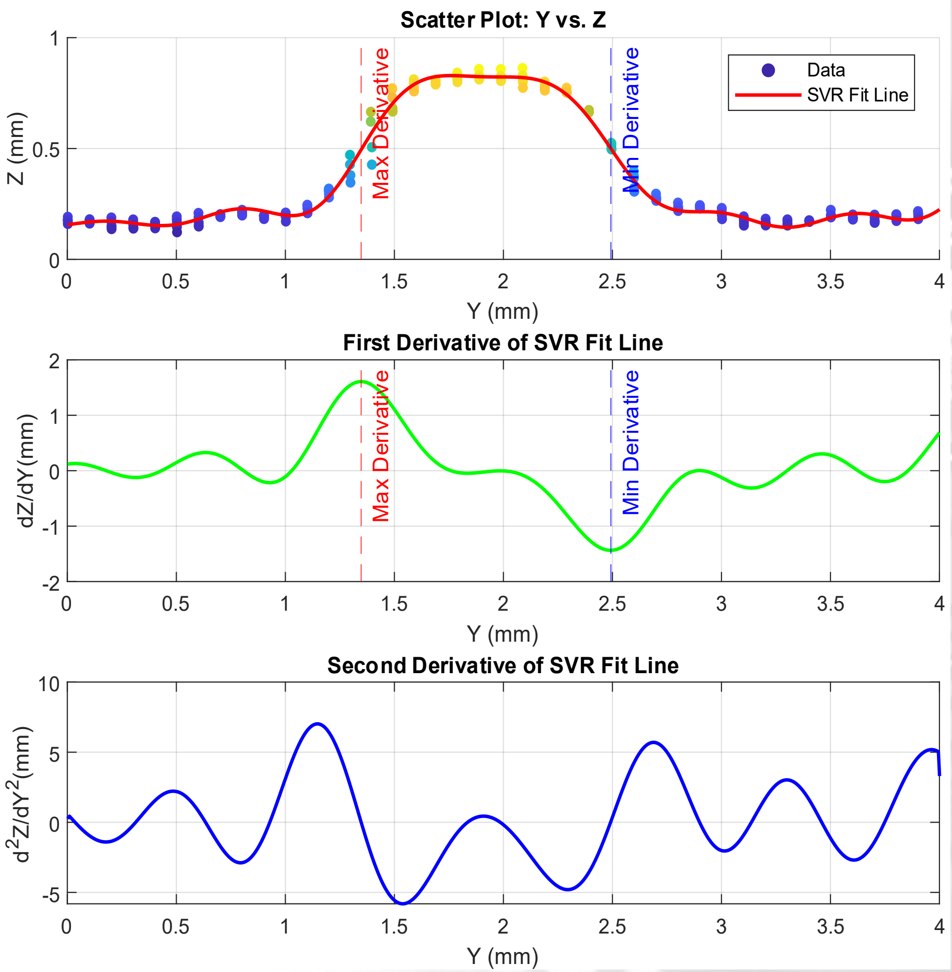
(e) Rotate point cloud using tilt angle to align YZ-data points from start to end of track

(f) Denoised point cloud with initialized coordinates



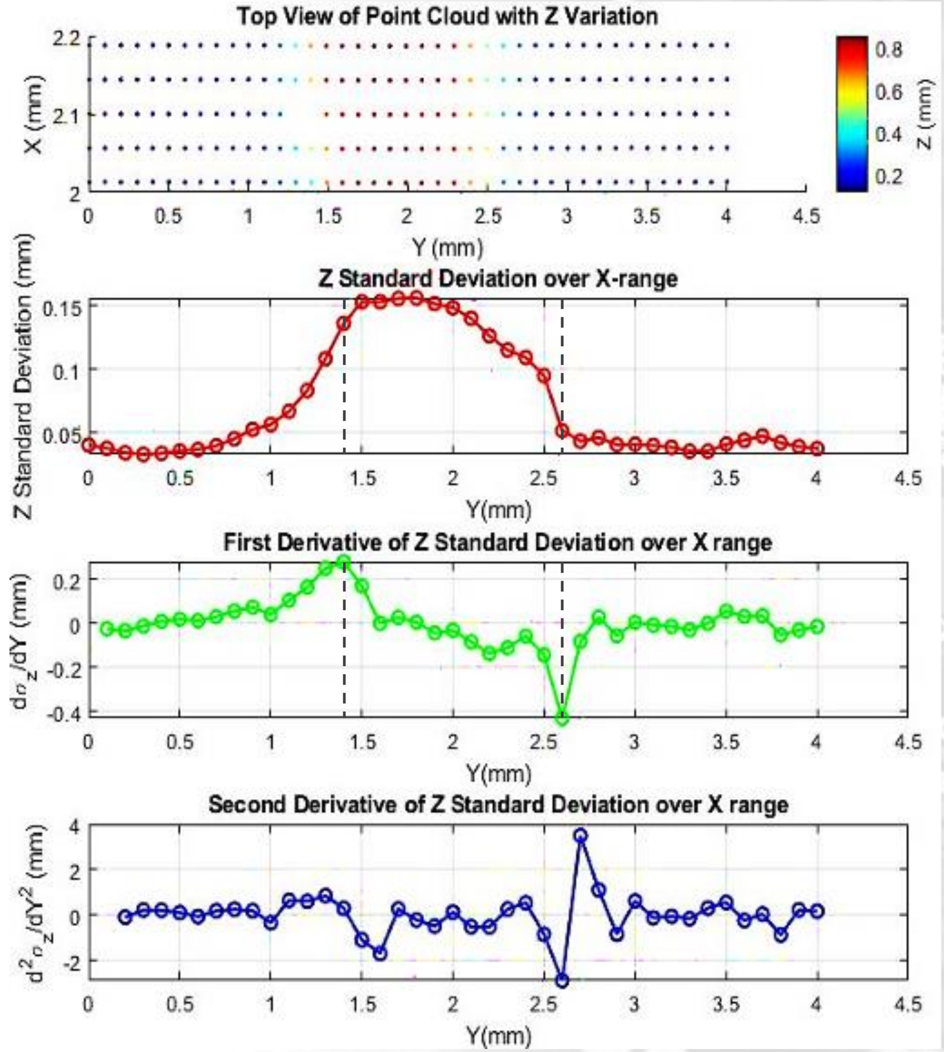
Evaluation of Track Width from Point Cloud Scans

1. Assess the cross-sectioned X-range from the front (YZ-field of view).
2. Fit a Support Vector Regression (SVR) line to the collective data points.
3. Plot the first-derivative of the SVR fit line and determine the global maxima and minima corresponding to the points where the track intersects with the substrate from both sides.
4. Track Width = Difference in Y, where global maxima and global minima exist.



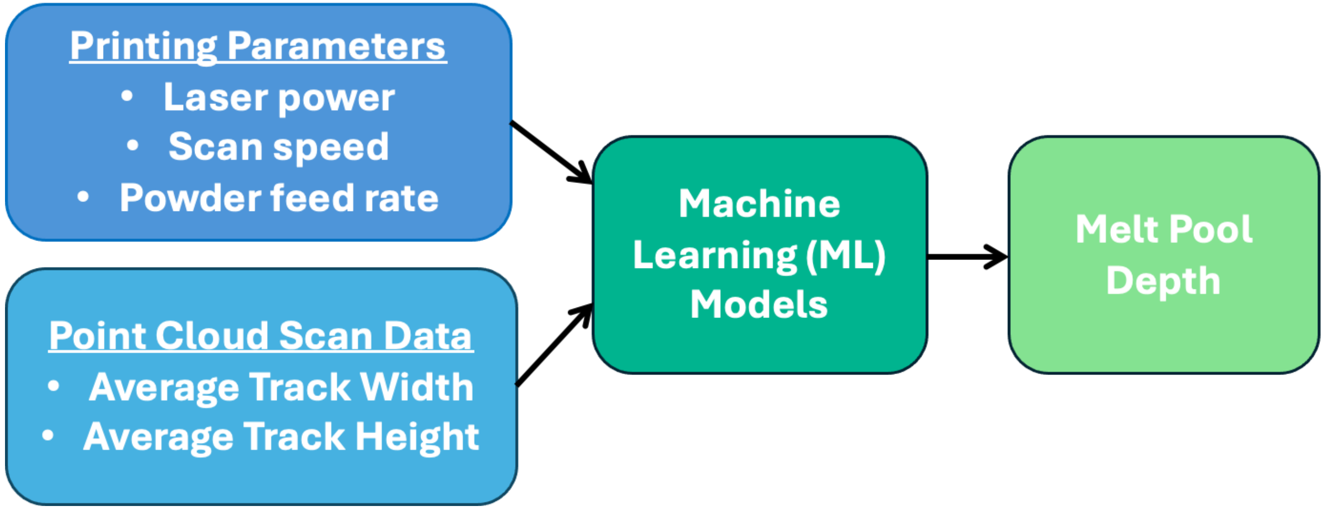
Evaluation of Track Height using Point Cloud Data

1. Asses the cross-sectioned X-range from the top (XY-field of view).
2. Examine all distributed data points and evaluate their standard deviation in the Z-direction.
3. Plot the first-derivative of the Z-standard deviation over the X-range and determine the global maxima and minima.
4. Identify the Z-values of the cross-sectioned point cloud that correspond to the Y-values at those maxima and minima, naming them (z_at_maxima and z_at_minima).
5. Track Height = Difference between the lower Z-value amongst the two (z_at_maxima or z_at_minima) and the point cloud's maximum Z-value.



ML Models for Melt pool Depth Estimation

- ***Objective:* Train ML models to predict the melt pool depth.**
- Trained models: Linear Regression (LR), Decision Tree (DT), Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Neural Networks (NN).
- Dataset split (**70% training, 30% testing** to validate model generalization).
- **Mean Absolute Error (MAE)** and **Root Mean Square Error (RMSE)** were used to rate the prediction performance of the regression models.



$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|C_{mi} - C_{pi}\right|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(C_{mi} - C_{pi}\right)^2}$$

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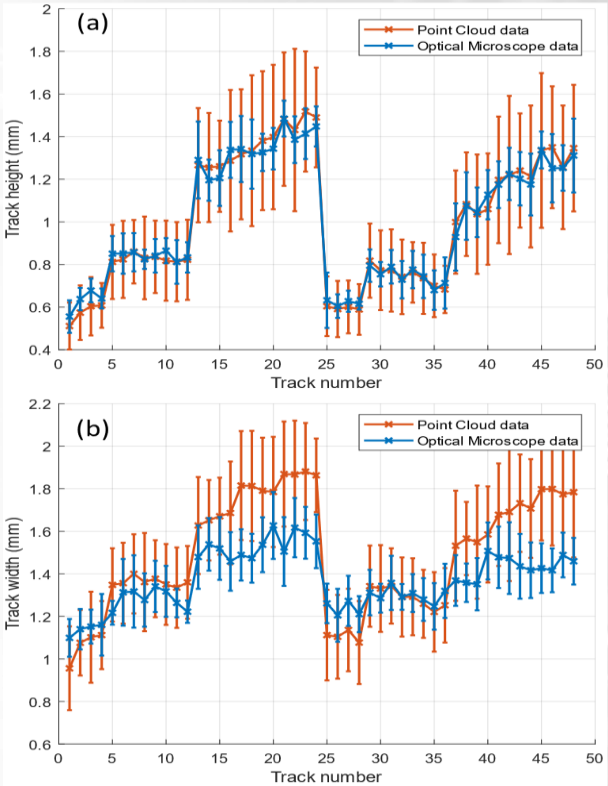
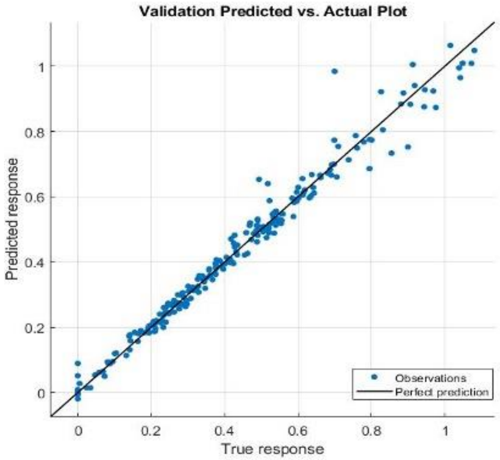
Results: Melt pool Depth Prediction

- There is a good agreement between the measured track width and height from point cloud using automated processing steps and the ground truth measurements obtained using an Optical Microscope.
- Gaussian Process Regression (GPR) resulted in **best performance.**
- **Study Outcome:**
  - Improved ML model performance by incorporating track width and height from point cloud data, resulting in a **63.78% reduction in MAE and a 19.9% in RMSE** compared to exclusive reliance on process parameters.



Model Used	Train MAE (μm)	Train RMSE (μm)	Test MAE (μm)	Test $RMSE$ (μm)
Linear Regression	65.76	67.62	52.20	71.03
Decision Tree	51.77	75.82	44.10	64.10
SVR (linear)	48.45	67.82	49.36	71.46
SVR (Quadratic)	29.30	48.78	26.29	34.33
GPR (Exponential)	**23.25**	**38.19**	**18.89**	**25.50**
Neural Network	31.99	47.62	27.91	37.59



GPR Model Inputs	MAE(µm)	RMSE(µm)
Laser Power, Scan Speed, Powder Feed Rate, Track Width, Track Height	18.89	25.50
Laser Power, Scan Speed, Powder Feed Rate	52.15	31.85

Conclusions and Future Work

- Point cloud data **significantly improves prediction accuracy over using only process parameters**, eliminating the need for destructive testing to determine melt pool depth.
- Specifically, the **GPR model's predictions of melt pool depth** had a mean absolute percentage error (MAPE) of around 4%, **indicating up to 96% accuracy**.
- Introduced a promising **automated approach** that removes the need for manual intervention in filtering and denoising point cloud scans.
- Future work will focus on **integrating real-time monitoring tools** to further improve prediction efficiency and accuracy.

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Supplementary Information

Gaussian Process Regression (GPR)

For a given set of observations y and inputs $\mathbf{X}$, the marginal likelihood $\mathcal{L}(y|\mathbf{X},\theta)$ is the probability of observing the data under the model with a given set of hyperparameters θ. In GPR, this likelihood is Gaussian, given by:

$$\mathcal{L}(y|\mathbf{X},\theta) = \mathcal{N}(y; 0, \mathbf{K} + \boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}\mathbf{I})$$

where:

- y is the vector of observed outputs,
- $\mathbf{K}$ is the covariance matrix defined by the kernel function $k(\mathrm{x}_i, \mathrm{x}_j)$ for the inputs $\mathbf{X}$,
- $\boldsymbol{\sigma}_{\boldsymbol{n}}^{\mathbf{2}}$ is the noise variance, and
- $\mathbf{I}$ is the identity matrix.

The exponential kernel, is defined by:

$$k(\mathrm{x}_i, \mathrm{x}_j) = \boldsymbol{\sigma}_{\boldsymbol{f}}^{\mathbf{2}} \exp(-\frac{\|\mathrm{x}_i - \mathrm{x}_j\|}{\ell})$$

where:

- $\boldsymbol{\sigma}_{\boldsymbol{f}}^{\mathbf{2}}$ is the signal variance (a hyperparameter)
- $\|\mathrm{x}_i - \mathrm{x}_j\|$ is the Euclidean distance between the input points x_i and x_j,
- ℓ is the length scale (a hyperparameter)