08/14/2019
SFF 2019
0935 hrs
Rm. 412

Using Heterogeneous In-process Sensor Data To Detect Lack-of-fusion Defects In Directed Energy Deposition of Titanium Alloy (Ti-6Al-4V) Parts

Mohammad Montazeri
Abdalla Nassar, Ph.D.
Christopher Stutzman
Prahalad Rao, Ph.D.

rao@unl.edu
Mechanical and Materials Engineering
University of Nebraska-Lincoln

PennState
Applied Research Laboratory

Acknowledgements

Penn State Funding

Office of Naval Research, under Contract No. N00014-11-1-0668

Air Force Research Laboratory through America Makes under agreement number FA8650-12-2-7230.

University of Nebraska-Funding

National Science Foundation (NSF).

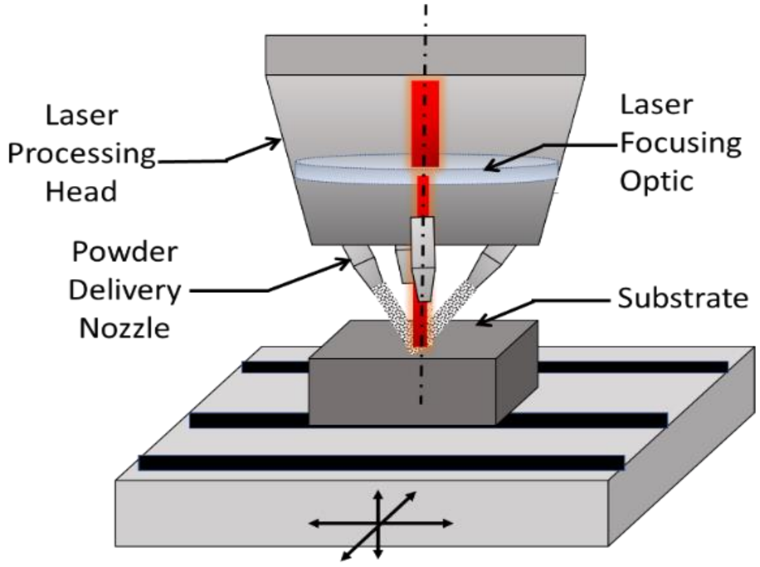
CMMI 1752069

The data for this work was generated at Penn State CIMP-3D by Dr. Abdalla Nassar, Mr. Chris Stutzman, and Dr. Edward Reutzel

PennState Applied Research Laboratory

CIMP-3D

Stutzman, C. B. , Nassar, A. R. , and Reutzel, E. W. , 2018, " Multi-Sensor Investigations of Optical Emissions and Their Relations to Directed Energy Deposition Processes and Quality," Additive Manufacturing, 21, pp. 333–339.

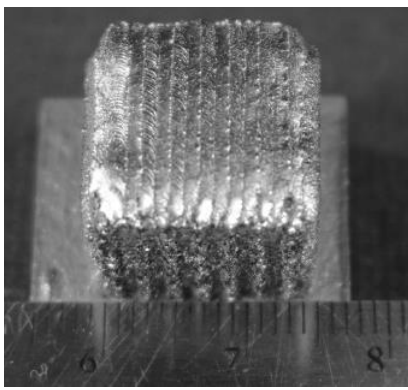


Detect flaws in DED parts using sensor data

Using a mathematical approach called Kronecker Product of Graphs

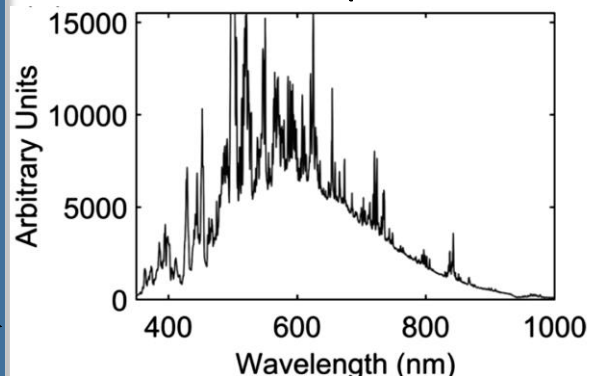
The Problem

Ascertain the part quality layer-by-layer using in-process sensor data.

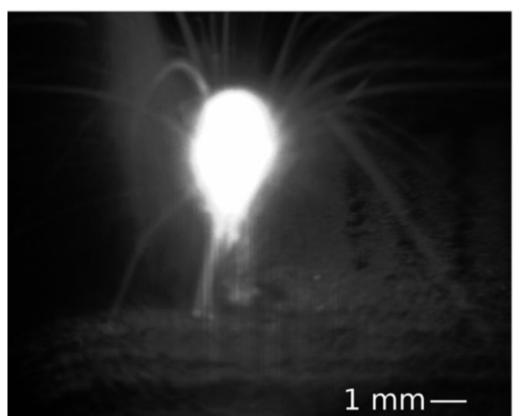


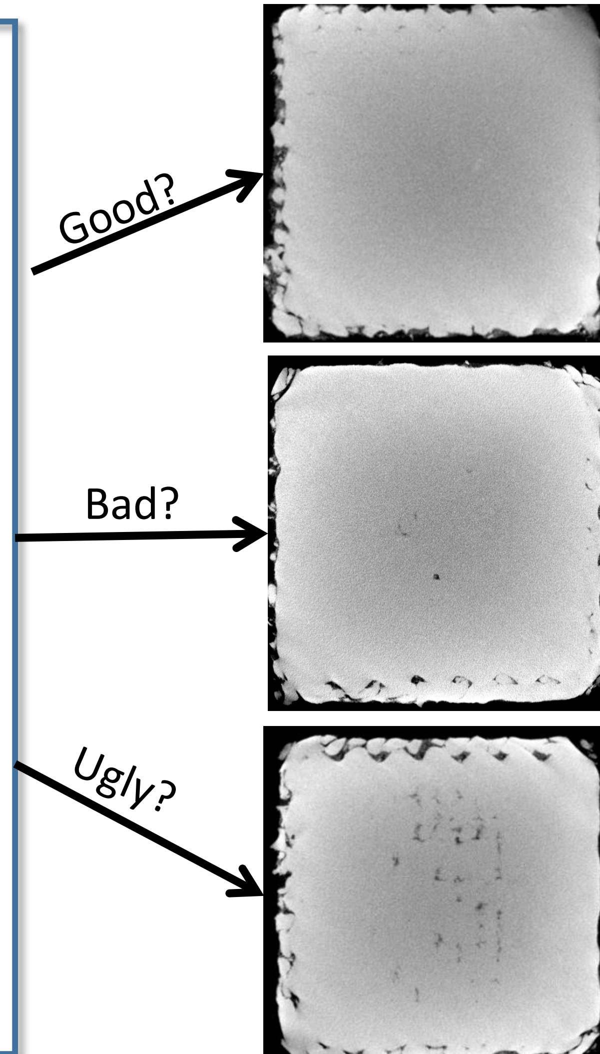
Ti-6-Al-4V
DED coupons

Meltpool optical emission spectrum



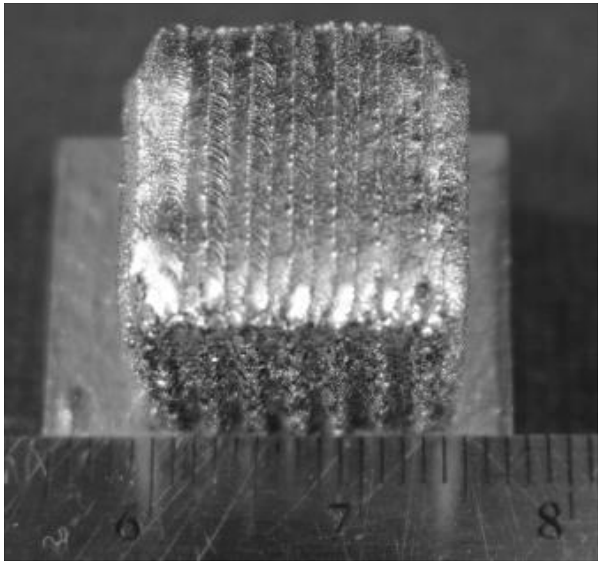
Meltpool plume images





Experimental Details

- Powder: Ti-6Al–4V
  - Spherical, argon argon-atomized powder with a D50 of 37.72 µm.
- Part Geometry: 15 mm ×15 mm ×10 mm (L × W × H)

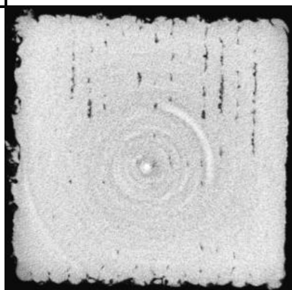
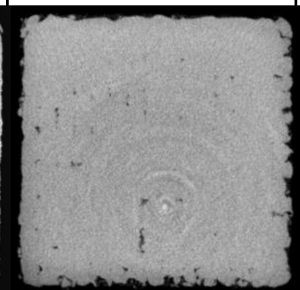
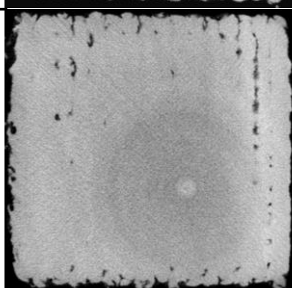
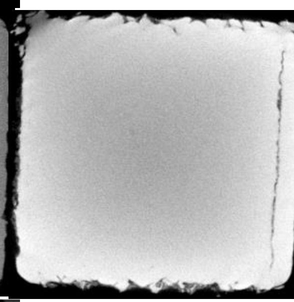
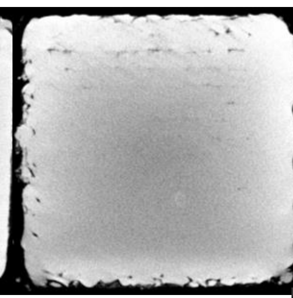
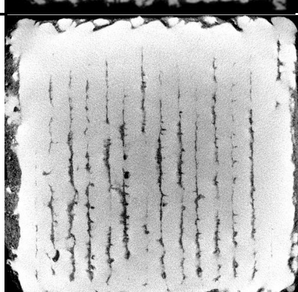
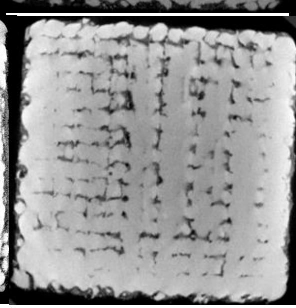
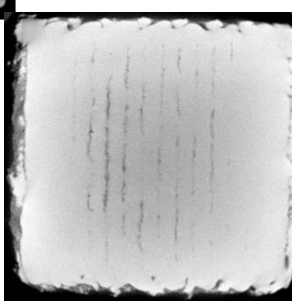
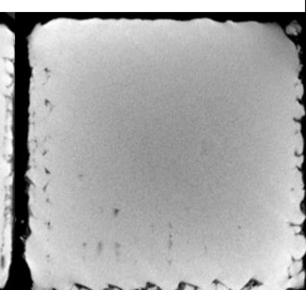


Post-build image of one test coupon, scale is in cm

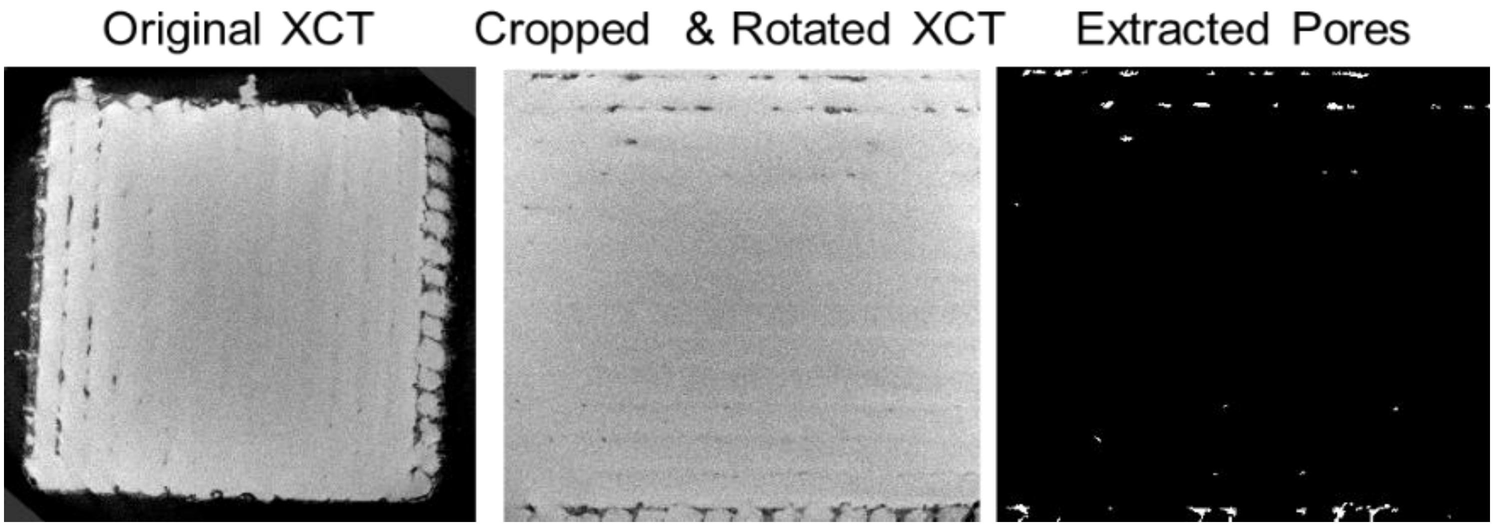
Fixed Printing Parameters (Optomec LENS MR-7)

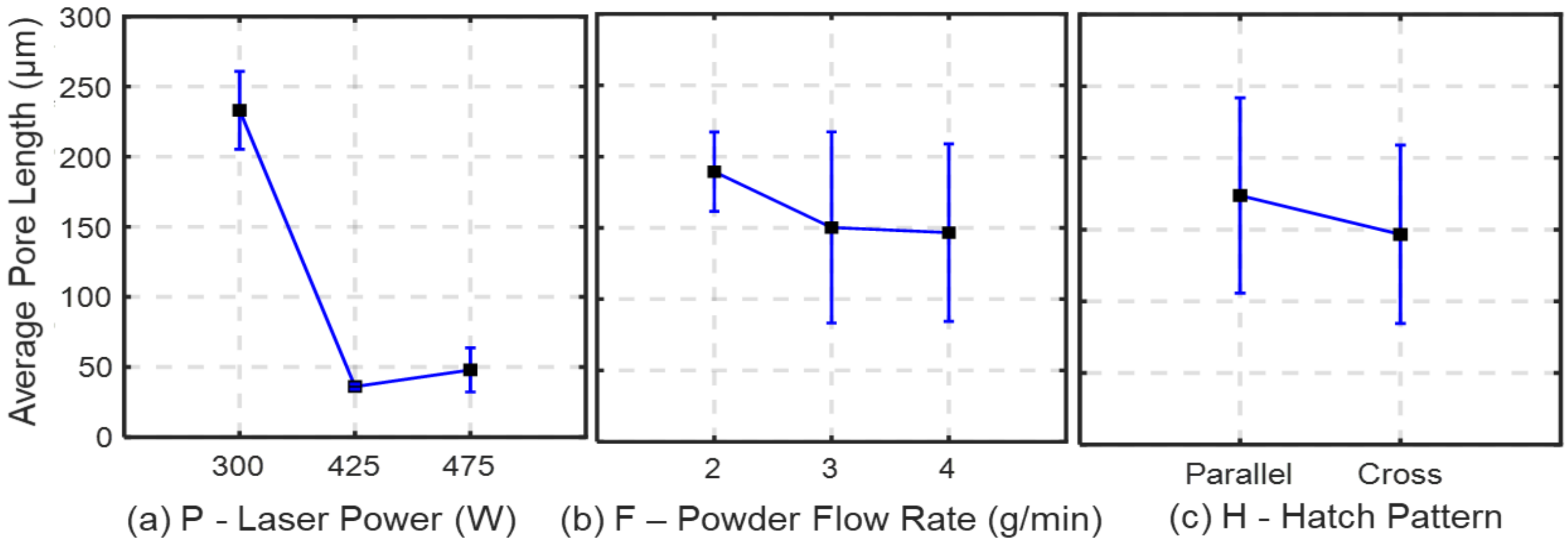
Parameter	Value
Speed (mm/s)	10
Layer Spacing (mm)	0.254
Hatch Spacing (mm)	1
Hatches per Layer	12
Layer per sample	40
Laser beam Diameter	1.24 mm

XCT of Printed Part

		Laser Power (Watts)					
		300W		425W		475W	
Hatch Pattern		parallel	cross	parallel	cross	parallel	cross
Powder Flow Rate (g/min)	2						
	3						
	4						

Statistical Analysis of the Data





Laser power has the most significant effect

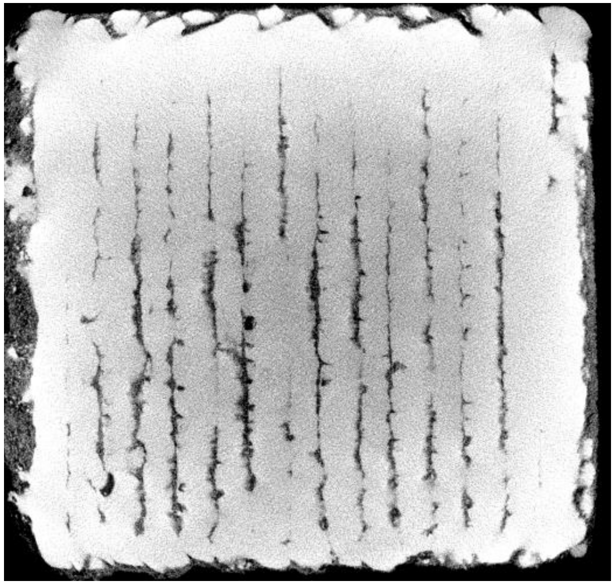
Random flaws occur even under optimal conditions.

Printing Parameters

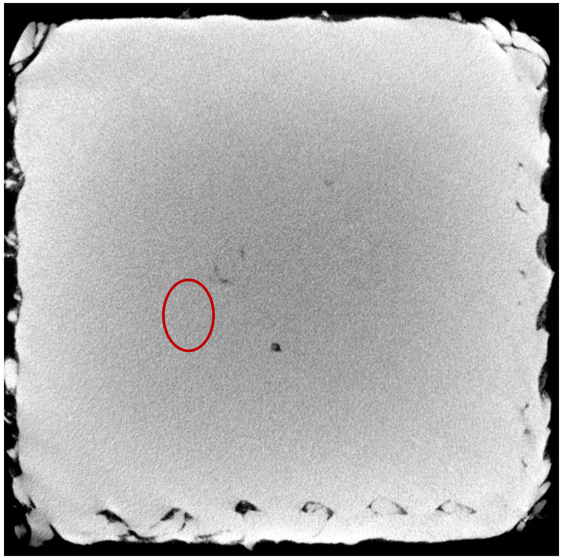
- Laser Power: 300 W
- Powder Flow Rate: 4 g/min
- Hatch Pattern: Parallel

Printing Parameters

- Laser Power: 475 W
- Powder Flow Rate: 4 g/min
- Hatch Pattern: Cross



Systematic flaw

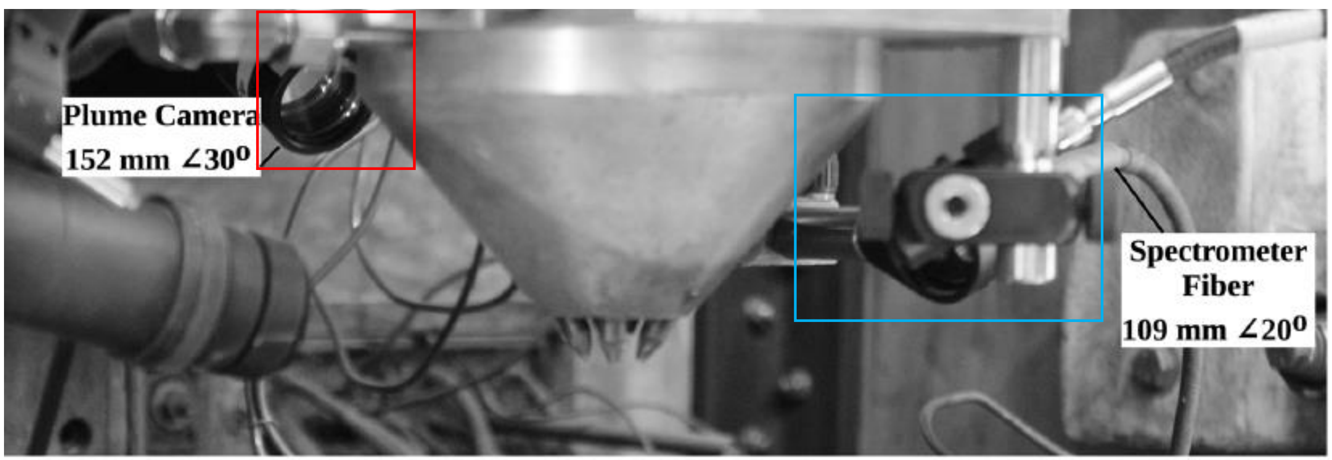


Random flaw

There is a need to detect the onset of defects using in-process sensor data.

Sensing Setup

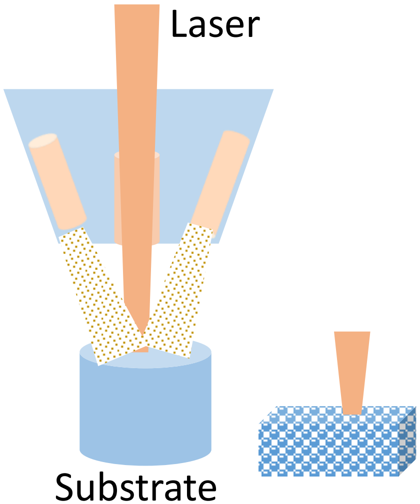
- Ocean optics HR2000 + UV-VIS-IR spectrometer
  - 20 ms integration time (50 Hz)
  - An optical fiber to couple light to the spectrometer
- Basler Pilot piA640-210gm CCD camera (Plume imaging)
  - 10 ms exposure time, 20 ms/frame (50 frames/second)
  - Coupled with a 430 nm band-pass filter

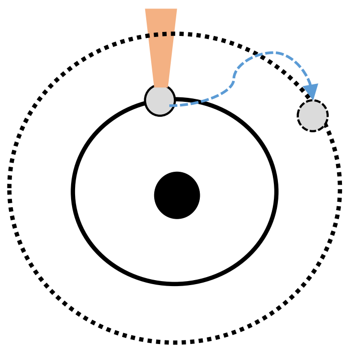


Photograph of the sensing setup at Penn State

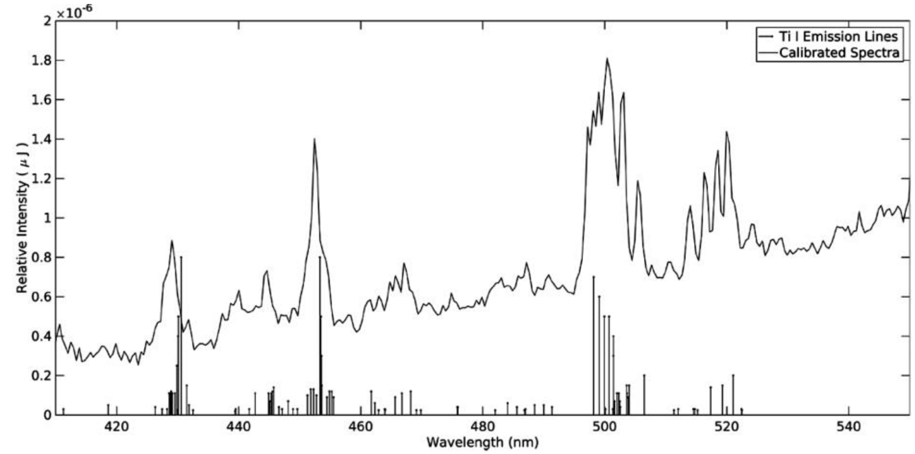
One frame of plume camera

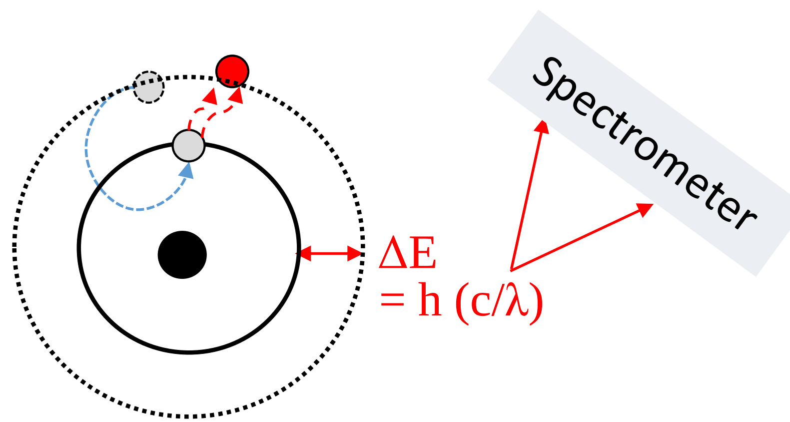
A Brief Primer to Optical Emission Spectroscopy





Electron transitions to higher energy orbit by absorbing energy from the laser.





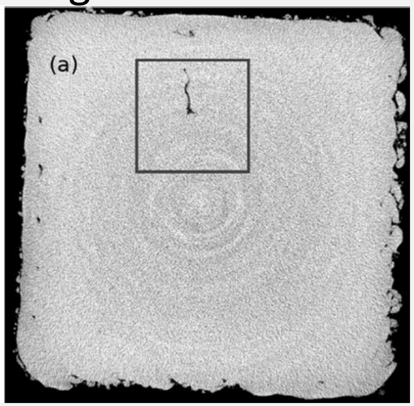
Electron transitions back to lower energy orbit. Emits a photon.

Sample Data

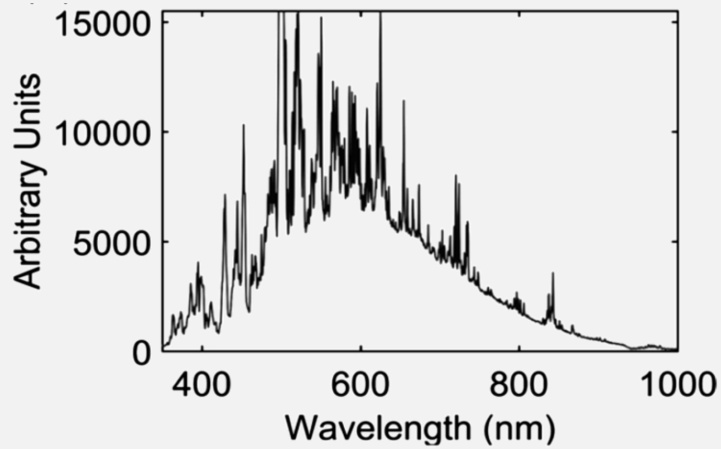
The key is to interpret the data in real-time as the part is being built.

425 W, 2 g/min, Cross hatching

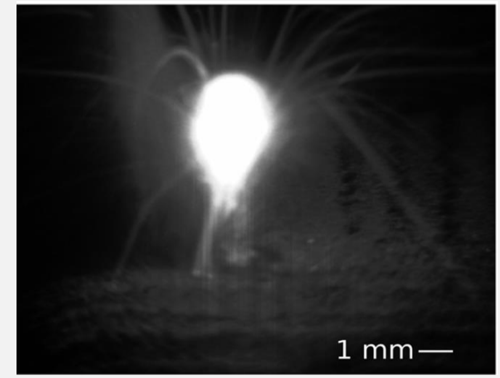
Region with flaw



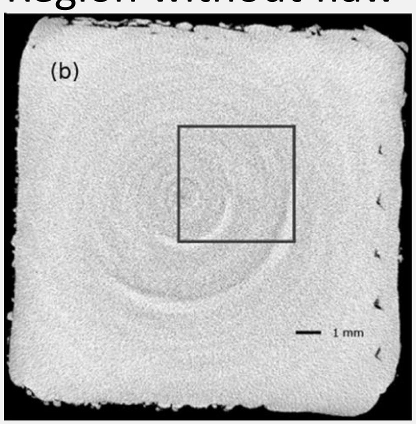
Spectrometer output

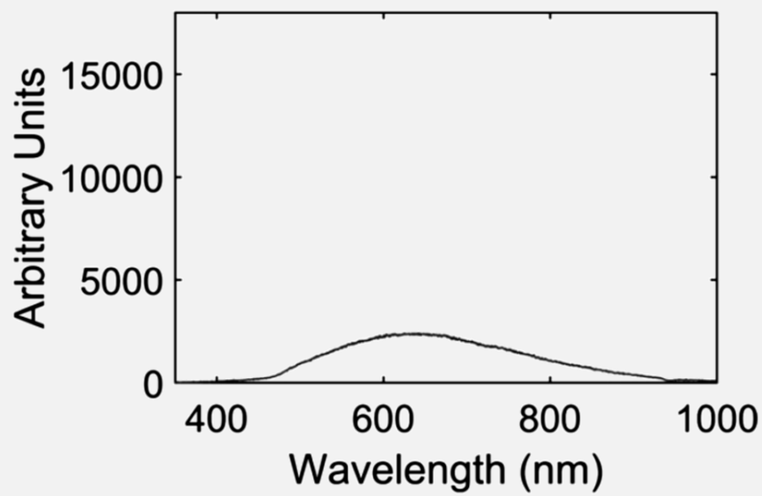


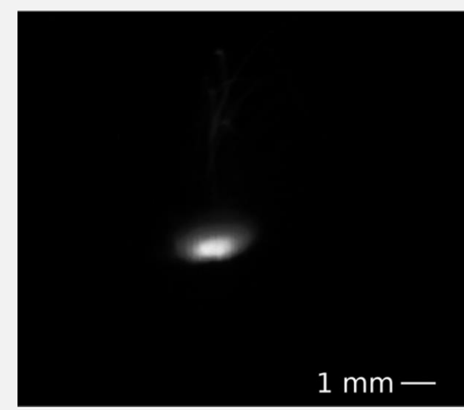
Plume camera output



Region without flaw

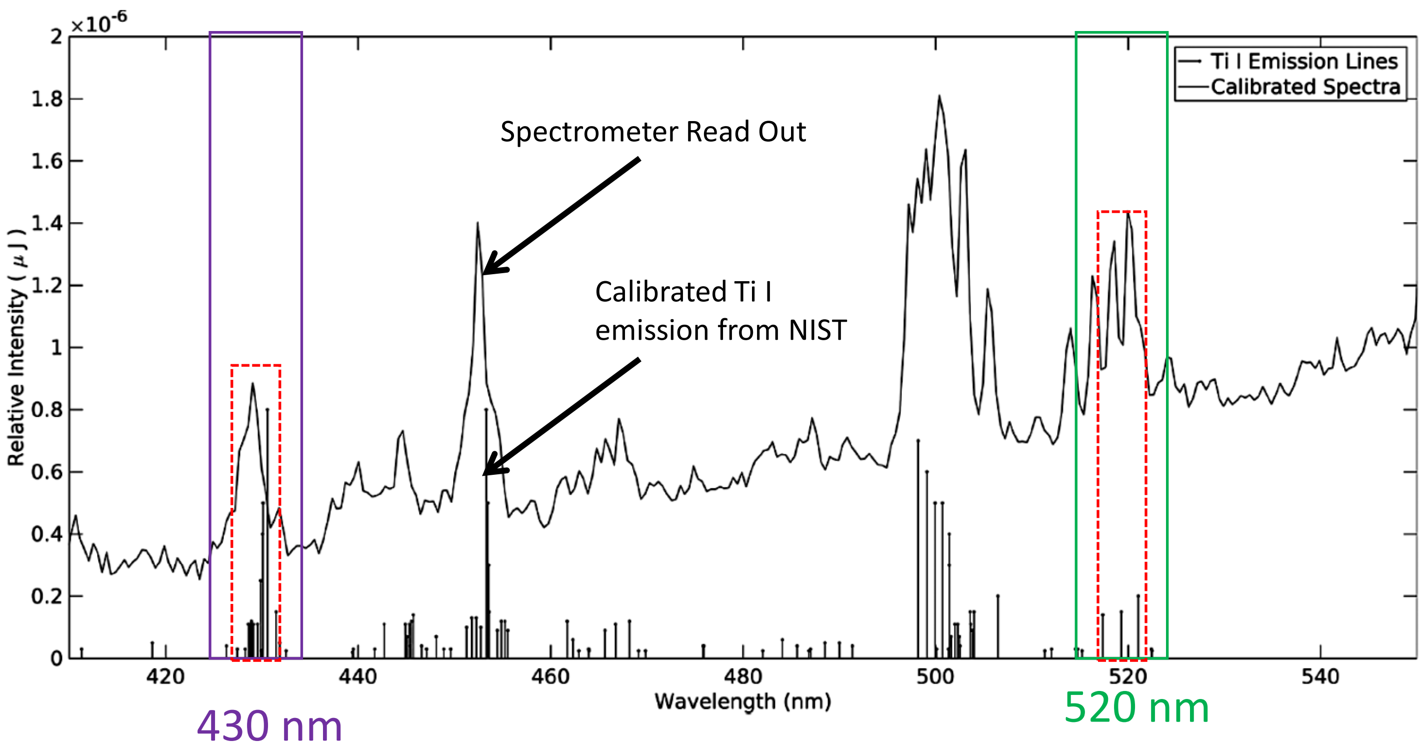






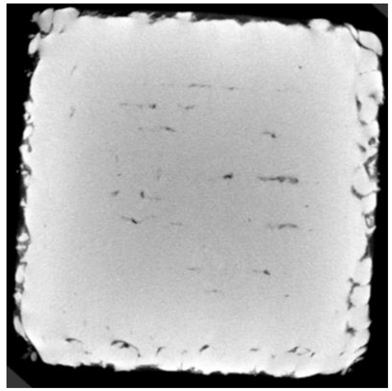
Extracting Features from the spectrometer signature

Extract the Line to continuum (L2C) ratio around two separate line emission 430 nm line & 520 nm line emissions corresponding to Titanium I (Ti I) spectra

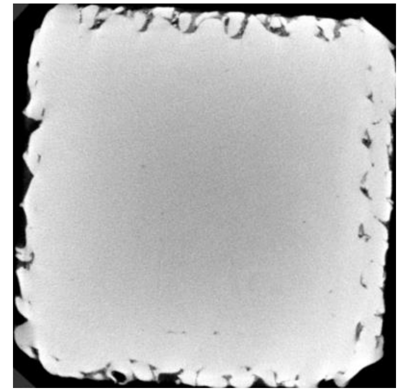


Real-world signals are complex and noise prone

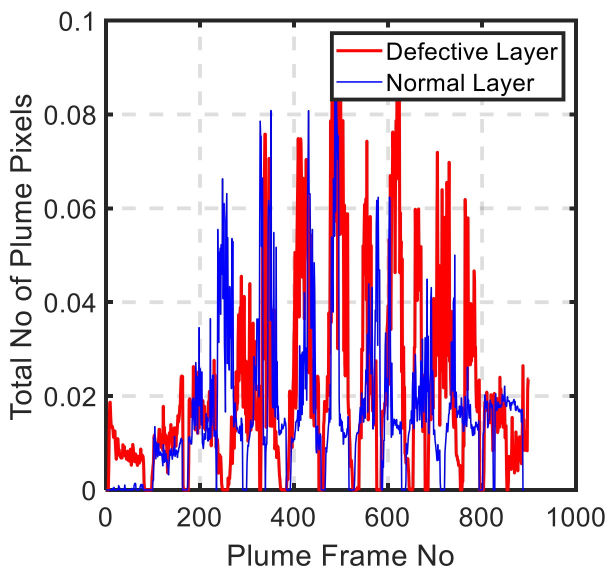
XCT for a defective layer



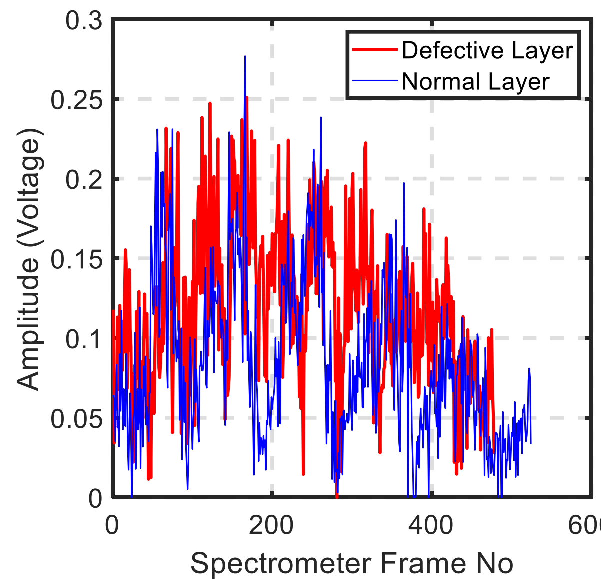
XCT for a normal layer



Overlaid Plume Signals



Overlaid Spectrometer Signals



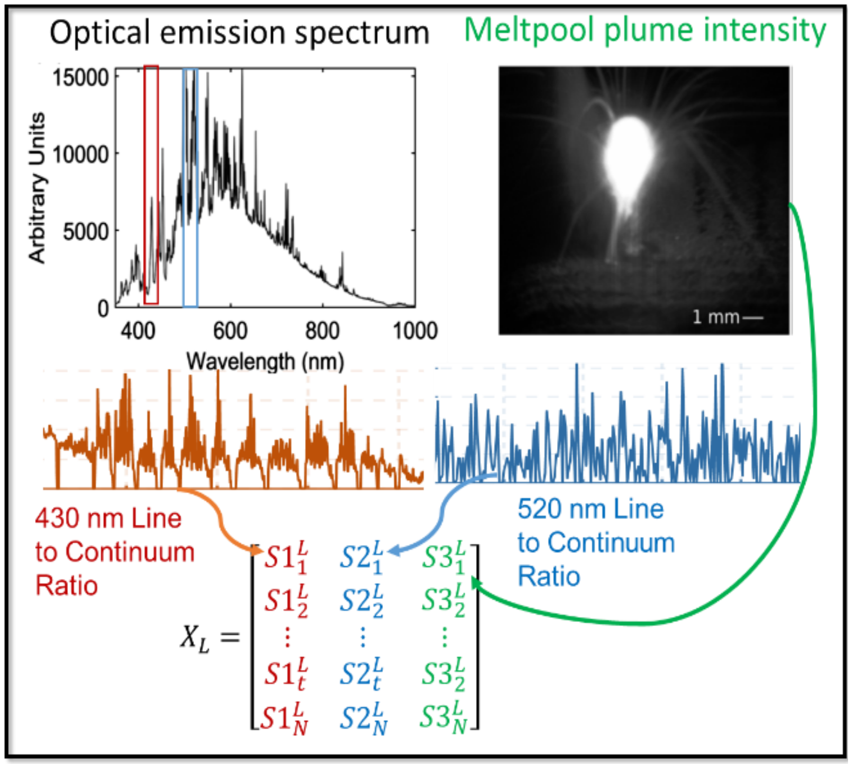
It is hard to differentiate between porous and non-porous printed layers based on the raw signal.

Key Idea

Detect a flaw by comparing the signal being captured to a known state.

Approach

Step 1: Combine data from multiple sensors in the form of a network graph.

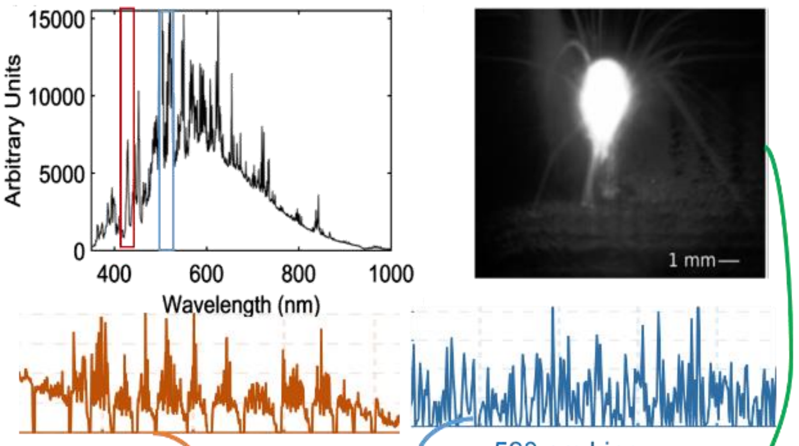


Store all the information about a layer in a matrix.

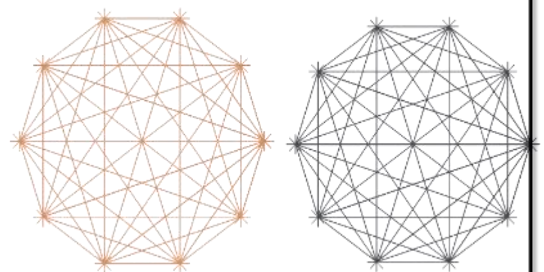
Approach

Step 1: Combine data from multiple sensors in the form of a network graph.

Step 2: Build a dictionary of signal patterns through the Kronecker product of graphs



$$X_L = \begin{bmatrix} S1_1^L & S2_1^L & S3_1^L \\ S1_2^L & S2_2^L & S3_2^L \\ \vdots & \vdots & \vdots \\ S1_t^L & S2_t^L & S3_2^L \\ S1_N^L & S2_N^L & S3_N^L \end{bmatrix}$$



Dictionary from the Kronecker Product

$$D_c = \begin{bmatrix} k(G_1 \otimes G_1) & \cdots & k(G_1 \otimes G_N) \\ \vdots & \ddots & \vdots \\ k(G_N \otimes G_1) & \cdots & k(G_N \otimes G_N) \end{bmatrix}$$

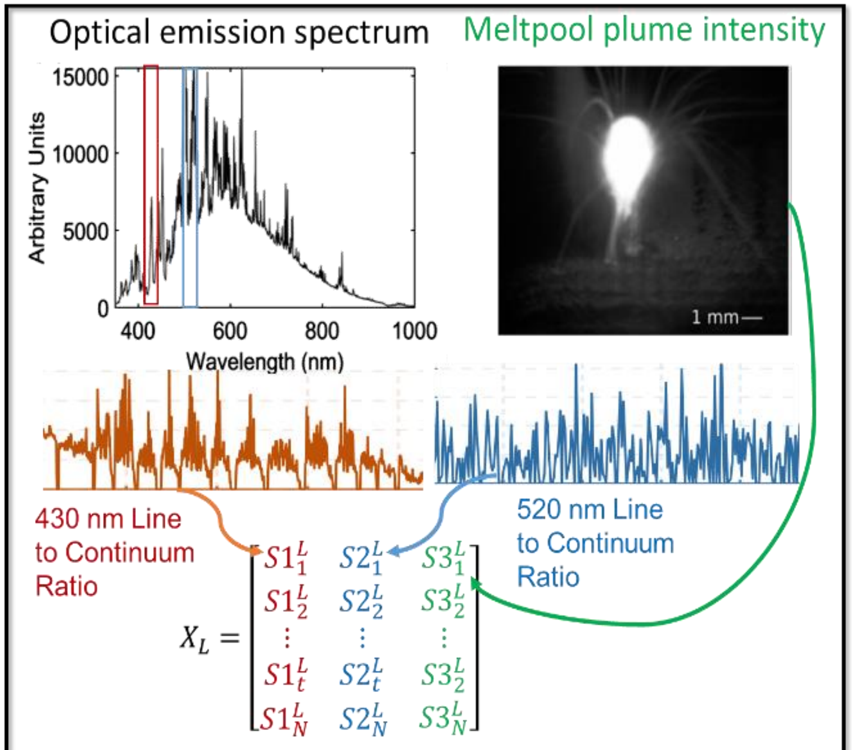
- Compare the information from a layer with all the layers.
- This is a record of how all layers of a part relate to each other (dictionary)
- If a part is good, its dictionary will “look” different than that of a bad part.

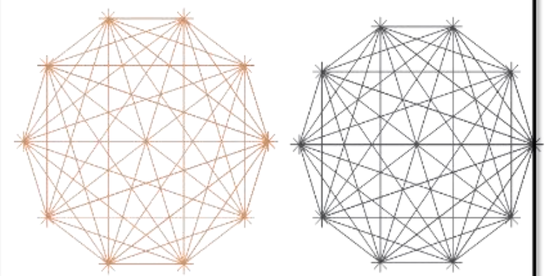
Approach

Step 1: Combine data from multiple sensors in the form of a network graph.

Step 2: Build a dictionary of signal patterns through the Kronecker product of graphs

Step 3: Use the dictionary to predict the severity of lack-of-fusion



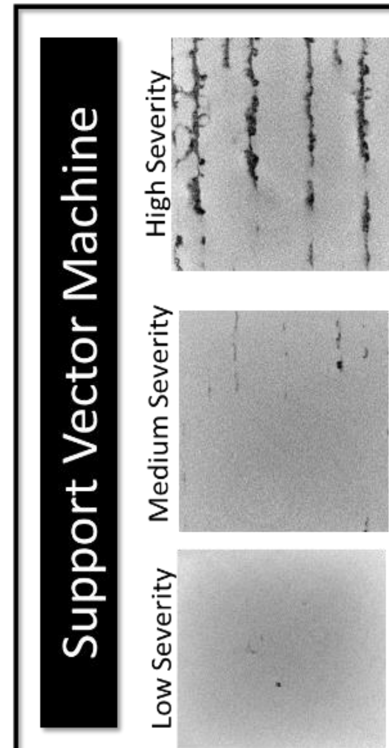


G_1
Graph of sensor data from of Layer 1

G_N
Graph of sensor data from Layer N

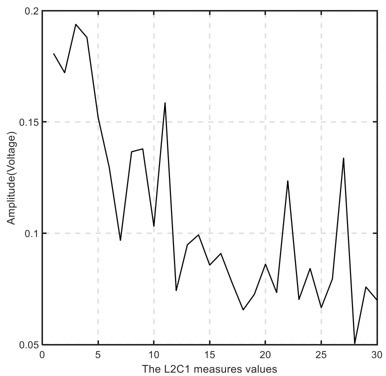
Dictionary from the Kronecker Product

$$D_c = \begin{bmatrix} k(G_1 \otimes G_1) & \cdots & k(G_1 \otimes G_N) \\ \vdots & \ddots & \vdots \\ k(G_N \otimes G_1) & \cdots & k(G_N \otimes G_N) \end{bmatrix}$$

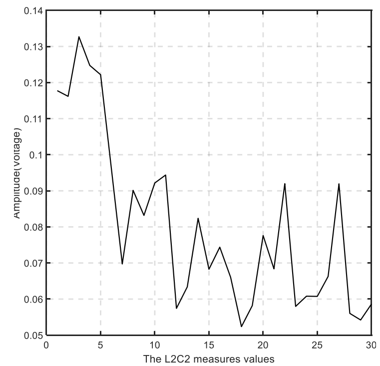


If given a signal (sentence), look up in which dictionary it belongs to.

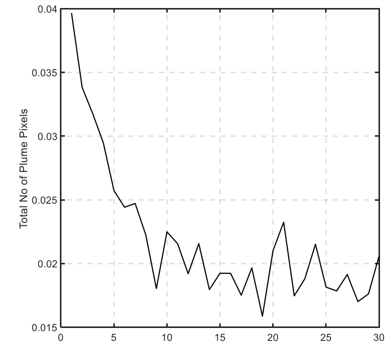
Step 1: Combining the signals from each layer as a graph



$$X_{\substack{Line\ to\ \ Continnum\ Ratio \\ 430\ nm}} = \begin{bmatrix} S1_1^L \\ \vdots \\ S1_N^L \end{bmatrix}$$



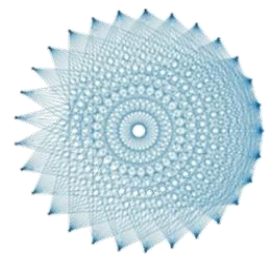
$$Y_{\substack{Line\ to\ \ Continnum\ Ratio \\ 520\ nm}} = \begin{bmatrix} S2_1^L \\ \vdots \\ S2_N^L \end{bmatrix}$$



$$Z_{Plume\ Area} = \begin{bmatrix} S3_1^L \\ \vdots \\ S3_N^L \end{bmatrix}$$

$$X_L = \begin{bmatrix} S1_1^L & S2_1^L & S3_1^L \\ S1_2^L & S2_2^L & S3_2^L \\ \vdots & \vdots & \vdots \\ S1_t^L & S2_t^L & S3_2^L \\ S1_N^L & S2_N^L & S3_N^L \end{bmatrix}$$

Graph (for layer *n*)



Making a graph out of Matrix

$$X_L = \begin{bmatrix} S1_1^L & S2_1^L & S3_1^L \\ S1_2^L & S2_2^L & S3_2^L \\ \vdots & \vdots & \vdots \\ S1_t^L & S2_t^L & S3_2^L \\ S1_N^L & S2_N^L & S3_N^L \end{bmatrix}$$

Pick two rows from X_L

$$\vec{r}_a^{\,L} = \begin{bmatrix} S1_a^L & S2_a^L & S3_a^L \end{bmatrix} \quad \vec{r}_b^{\,L} = \begin{bmatrix} S1_b^L & S2_b^L & S3_b^L \end{bmatrix}$$

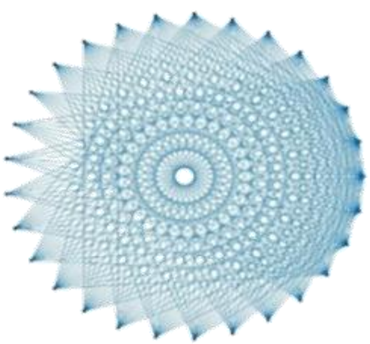
Obtain the difference between the two rows

$$w_{ab}^L = \left(\vec{r}_a^{\,L} - \vec{r}_b^{\,L}\right) C^{-1} \left(\vec{r}_a^{\,L} - \vec{r}_b^{\,L}\right)^{\mathrm{T}}$$

Put the result in a matrix

$$G_L = [w_{ab}^L]$$

Graph (for layer *n*)



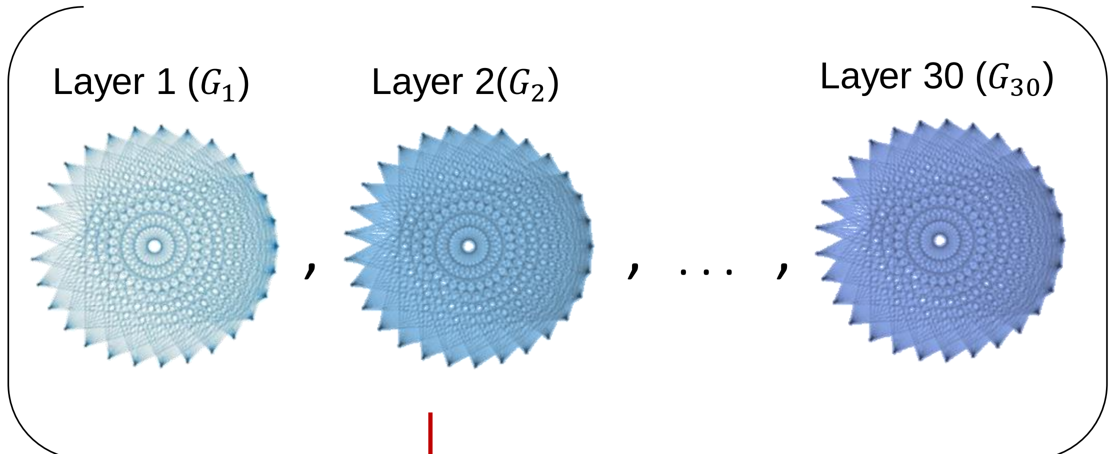
More graph theory

- Montazeri M, Yavari R, Rao P, Boulware P. In-Process Monitoring of Material Cross-Contamination Defects in Laser Powder Bed Fusion. ASME. *J. Manuf. Sci. Eng.* 2018;140(11):111001-111001-19. doi:10.1115/1.4040543. (Link)
- Montazeri M, Rao P. Sensor-Based Build Condition Monitoring in Laser Powder Bed Fusion Additive Manufacturing Process Using a Spectral Graph Theoretic Approach. ASME. J. Manuf. Sci. Eng. 2018;140(9):091002-091002-16. doi:10.1115/1.4040264. (Link)

Step 2: Creating a dictionary of all features

We create a dictionary from the first few (30) layers for each part.

Set of graphs for a part under known conditions =



$$\text{Dictionary } \mathrm{D_c} = \left[\begin{pmatrix} k(G_1, G_1) & \cdots & k(G_1, G_{30}) \\ \vdots & \ddots & \vdots \\ k(G_1, G_{30}) & \cdots & k(G_{30}, G_{30}) \end{pmatrix}\right]$$

Each row of the dictionary tells us how a layer compares to the other layers.

The Kronecker Product of Graphs

$$\text{Given, } X = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix};\ Y = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$$

$$X \otimes Y = \begin{bmatrix} X(1,1).Y & X(1,2).Y & X(1,3).Y \\ X(2,1).Y & X(2,2).Y & X(2,3).Y \\ X(3,1).Y & X(3,2).Y & X(3,3).Y \end{bmatrix}$$

$$X \otimes Y = \begin{bmatrix} 1.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & 0.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & 1.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \\ 0.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & 0.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & 1.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \\ 0.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & 1.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} & 0.\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \end{bmatrix}$$

Compare everything with everything.

The Kronecker Product of Graphs

$$\text{Dictionary } \mathrm{D_c} = \left[\begin{pmatrix} k(G_1, G_1) & \cdots & k(G_1, G_{30}) \\ \vdots & \ddots & \vdots \\ k(G_1, G_{30}) & \cdots & k(G_{30}, G_{30}) \end{pmatrix}\right]$$

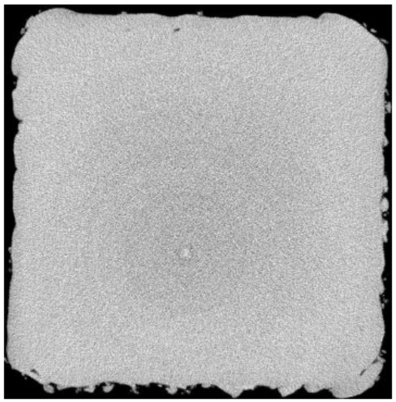
$$k\left(G_i \otimes G_j\right) = \sum_{\substack{\forall rows, \\ columns}} \left(\mathrm{I} - \gamma_{ij}\left(G_i \otimes G_j\right)\right)^{-1}$$

I is the identity matrix and $\gamma_{i,j}$ is the decay constant.

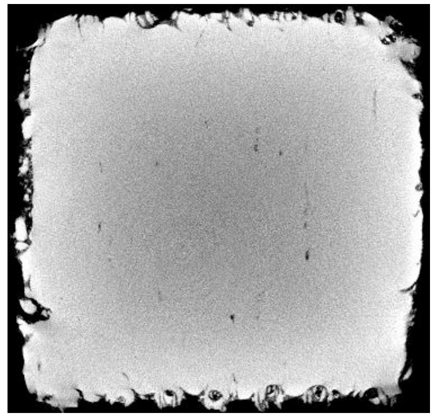
$\boxed{k\left(G_i \otimes G_j\right) \text{ is a number.}}$

Step 3: Predicting Porosity from the Online Sensor Data

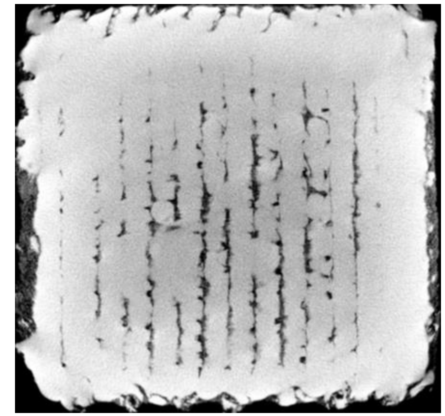
Low flaw probability
Avg. Pores Length for each layer < 50 µm



Medium flaw probability
50 µm < Avg. Pore Length < 200 µm



High flaw probability
Avg. Pores Length > 200 µm



A layer from the Dictionary D_c → Training of Classifier Algorithm →

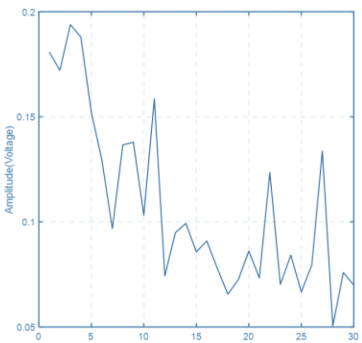
- Low: Avg. Pores Length for each layer < 50 µm
- Medium: 50 µm < Avg. Pores Length < 200 µm
- High: Avg. Pores Length > 200 µm

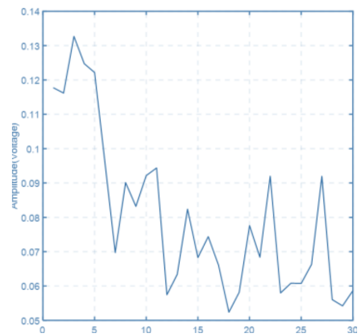
Row of Numbers

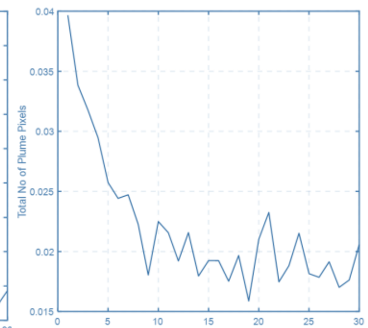
$$[(k(G_n, G_1)) \cdots k(G_n, G_{30})]$$

Predicting the layer quality on-the-fly

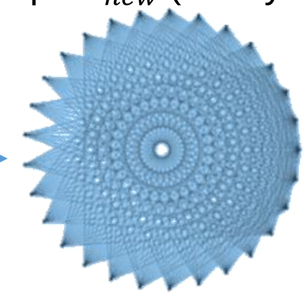
Convert a new signal for a new layer into a graph (< 0.5 sec)







Graph G_{new} (for layer *n* +*1*)

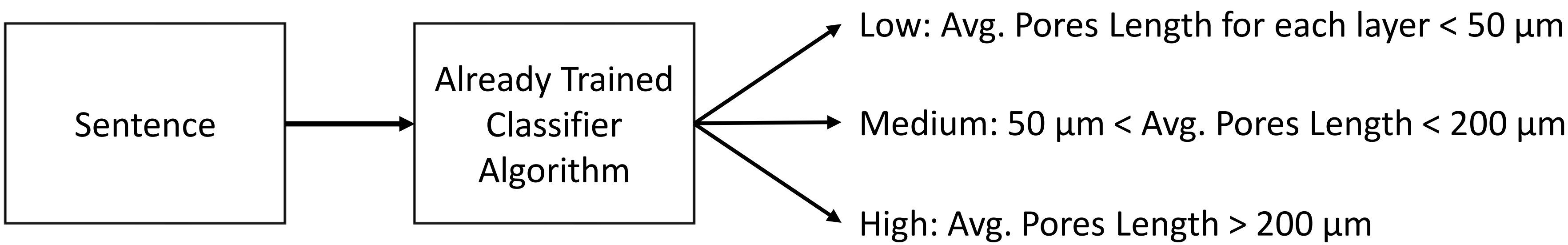


Predicting the layer quality on-the-fly

Convert the new signal into a sentence (< 2 seconds)

$$\theta_{new} = [k(G_{new} \otimes G_1) \quad \ldots \quad k(G_{new} \otimes G_N)]$$

Use the trained model for predicting porosity (< 1 second)



Lack-of-fusion Detection Results

True Classes ↓	Predicted Classes	
	Low Porosity x < 50 µm	High Porosity x > 50 µm
Low Porosity x < 50 µm	40 (out of 45)	5 (False Alarm)
High Porosity x > 50 µm	0 (Fail to detect)	55 (out of 55)

F-score ~ 95%

True Classes ↓	Predicted Classes		
	Low Porosity x < 50 µm	Medium 50 µ< x<200 µm	High Por. x > 200 µm
Low Porosity	40 (out of 45)	5 (False Alarm)	0
Medium Por.	0 (Fail to detect)	25 (out of 41)	16
High Por.	0 (Fail to detect)	0	14 (out of 14)

F-score ~ 75%

Conclusion

- Ability to identify the severity of an error with 75% accuracy (3-level case), in less than 5 sec.
- Traditional statistical-feature-based machine learning approach had fidelity of 35% to 40%.

University of Nebraska Lincoln

Nebraska Engineering Additive Technology Labs

LAMPS Laboratory for Advanced Manufacturing Processes and Sensing

Speaker Information

Reza Yavari
Mechanical and Materials Engineering

University of Nebraska-Lincoln
mrezayavari89@huskers.unl.edu

https://engineering.unl.edu/lamps/