

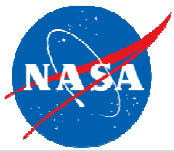
AI/ML defect detection in Selective Laser Melting (SLM) of Inconel 718

a step towards certification of SLM

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Activities to certify human-rated AM flight hardware

Foundational Work

Powder

Chemistry, Morphology,
Distribution

Recyclability

Builds

Thermal Processing

Material characterization

Characteristic defects / NDE

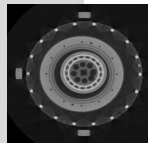
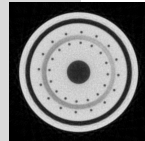
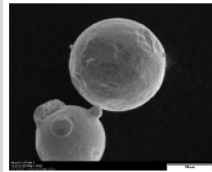
Surface finish improvement

Geometric dimensioning &
tolerancing / Thin sections

Quality

Build factor interactions

Machine-to-machine variability



Certification Tasks

Model Controls

Powder Controls

Material Property
Development

Build Execution Rqmts

Lot Acceptance
Methodology

Part Verification Rqmts

Proof test methodology

First article methodology

NDE / PODs

Part Development Plans

Flight Hardware

Space Launch System RS-25E

Trade study underway. IN718
ducts, nozzles, and baffles are
early candidates for print.

Launch 2023+



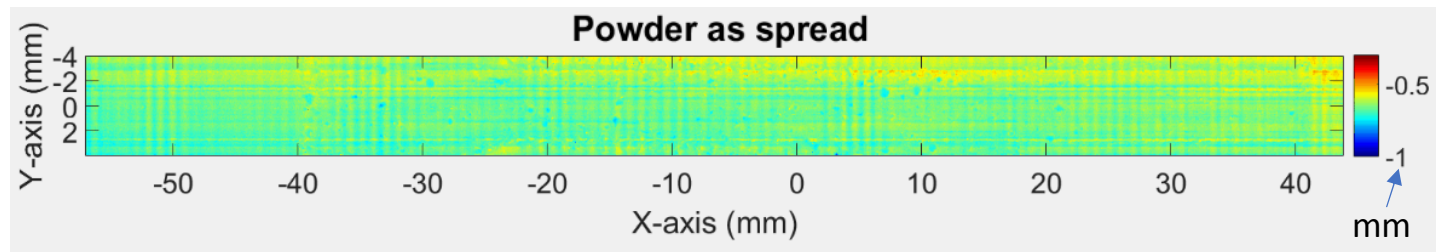
where Foundational Work directly supports Certification Tasks

In Situ profilometry

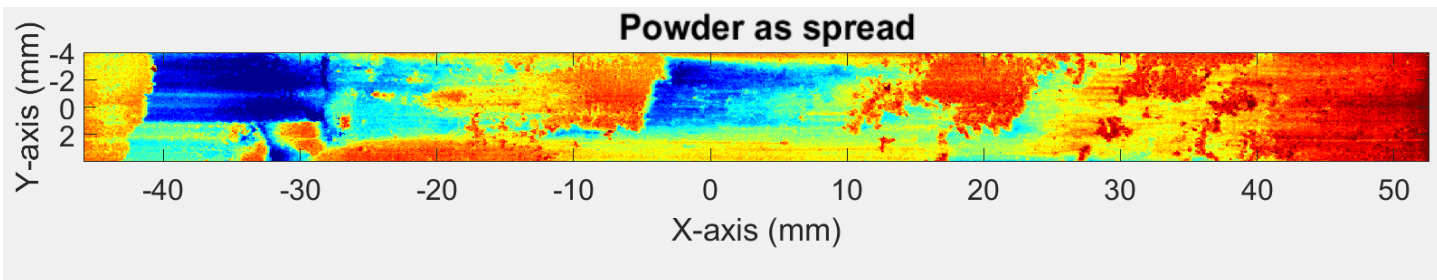
In Situ profilometry is capable of detecting poor powder spreading processes

- May be caused by bad powder (bottom-right image)
- Could be caused by a vibration (there is some in the top image, though it's not bad)

A nominal powder spread during fabrication of horizontal dog bone specimens



In this case, poorly sieved, used powder caused a bad powder spread in a subsequent build

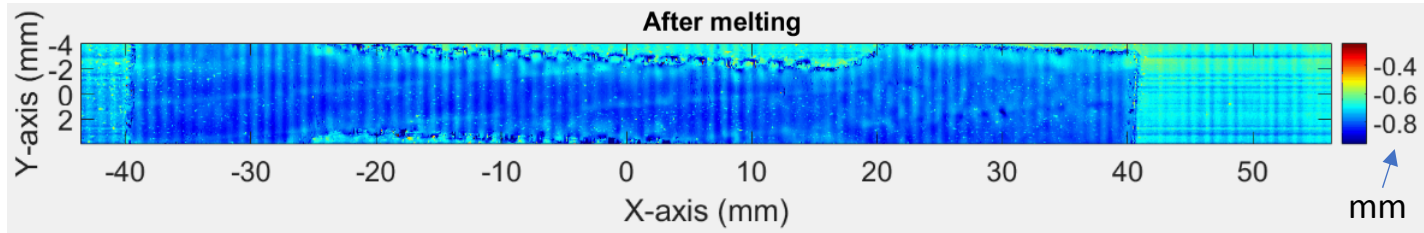


In Situ profilometry

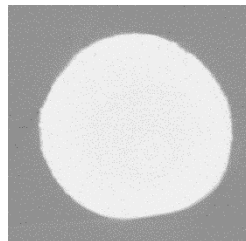
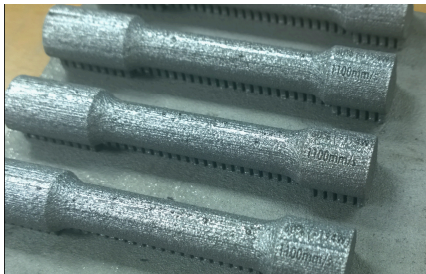
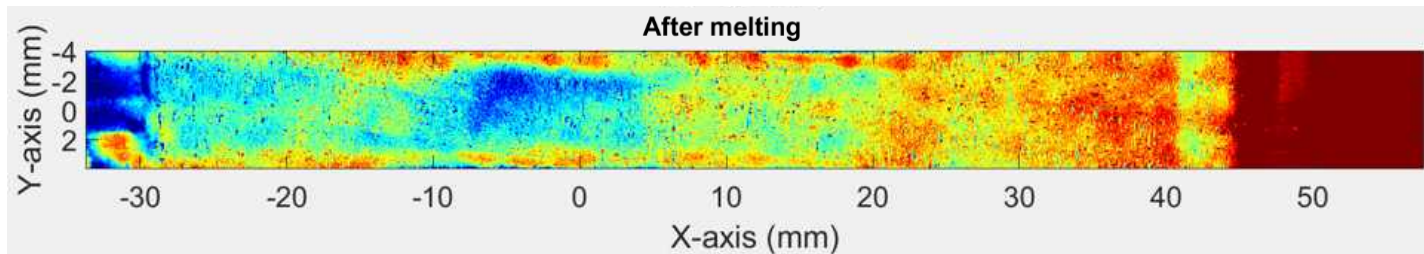
The melt corresponding to the nominal spread on the previous slide

Melting performance is also measured

- Good, dense parts are typically smooth and uniform
- Different surface roughness metrics can be used to identify various defect modes



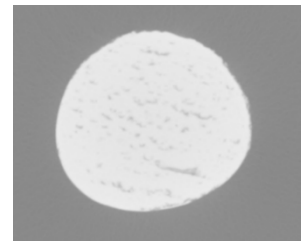
The bad powder leads to an uneven and rough melt, and likely a less dense part



Nominal

Much of the profilometry is accompanied by CT-scanning to validate results

Low density



In Situ visible imaging

Work in the Phase II and Phase II-X project has demonstrated that visible imaging of ejected powder particles is effective for determining build performance.

- This project is developing low-cost methods to obtaining the data
- Video is a great medium for big data analytics

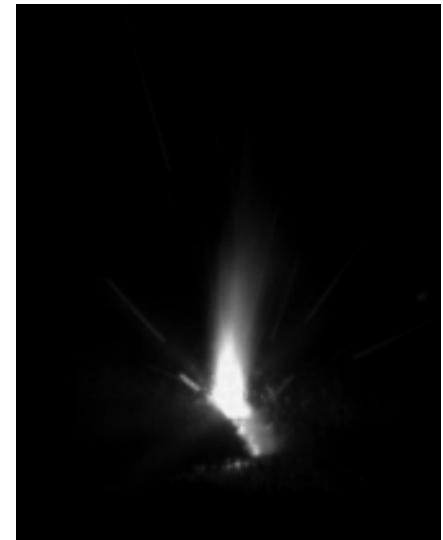


Low laser power

Visible imagery can track ejected particles to judge weld quality



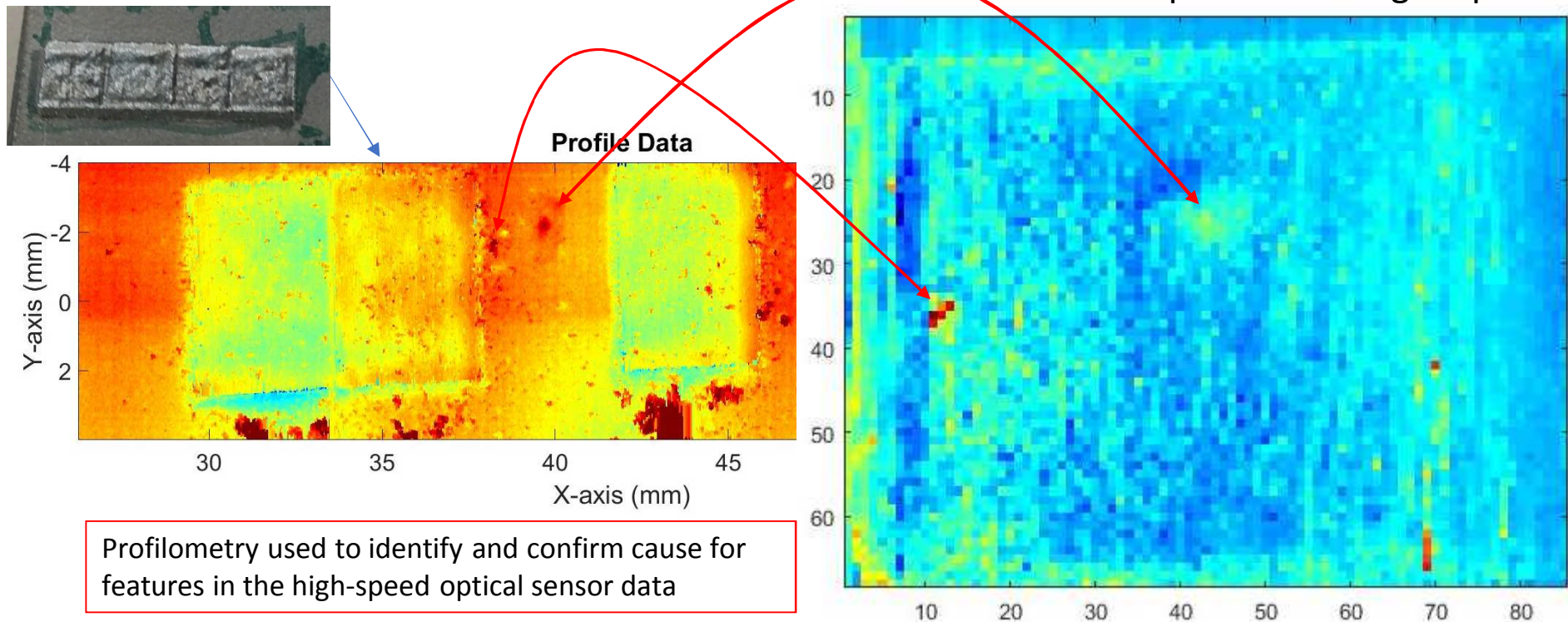
Defocused laser



Good (nominal) parameters

In Situ Spectroscopy

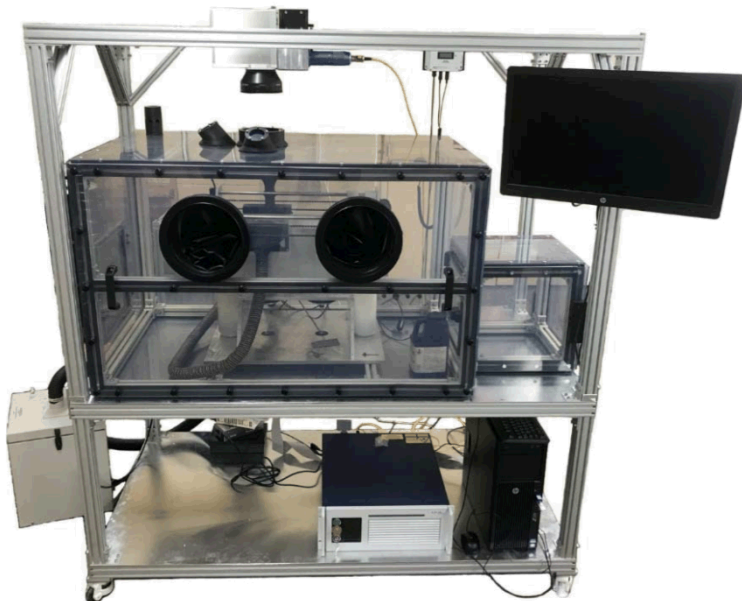
- UTCs in situ spectroscopy sensor identifies defects in the powder bed (confirmed with profilometry) and differences in powder layer thickness (denoted by the darker blue vs. teal areas in the image).
- This data is well suited for image processing-based data analytics and identifies a large number of build events



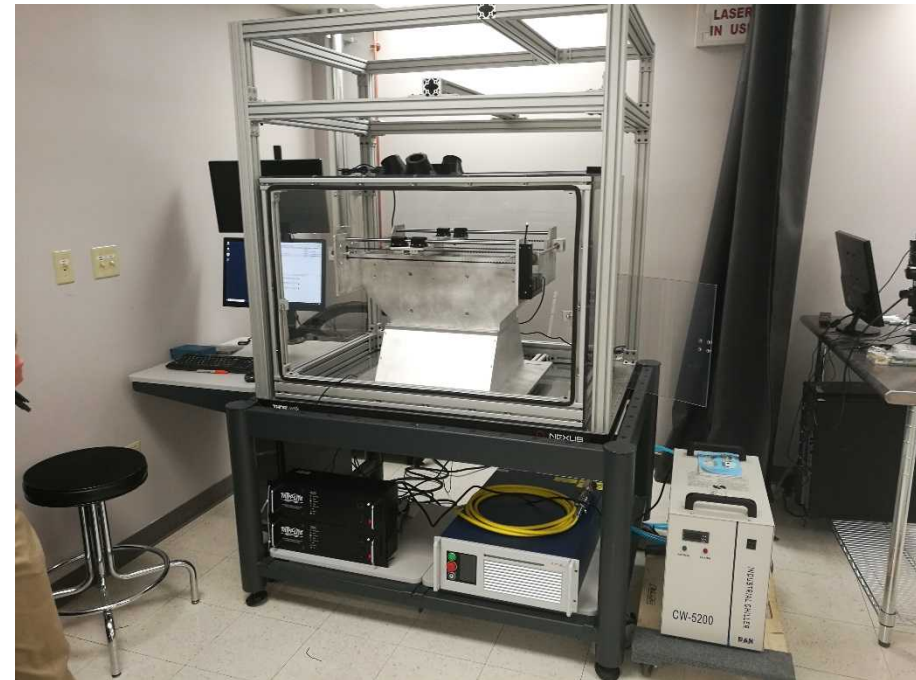
The OPENSLM LPBF system

- On this contract UTC is delivering their low-cost OPENSLM open-architecture laser powder bed fusion (LPBF) AM system to NASA LaRC, along with UTC's AMSENSE sensor system.
 - The Data Analytics group will be able to perform their own experiments and get their own data
 - The system gives full access to the build chamber and process parameters

Similar, completed version of OPENSLM at the University of Dayton Research Institute

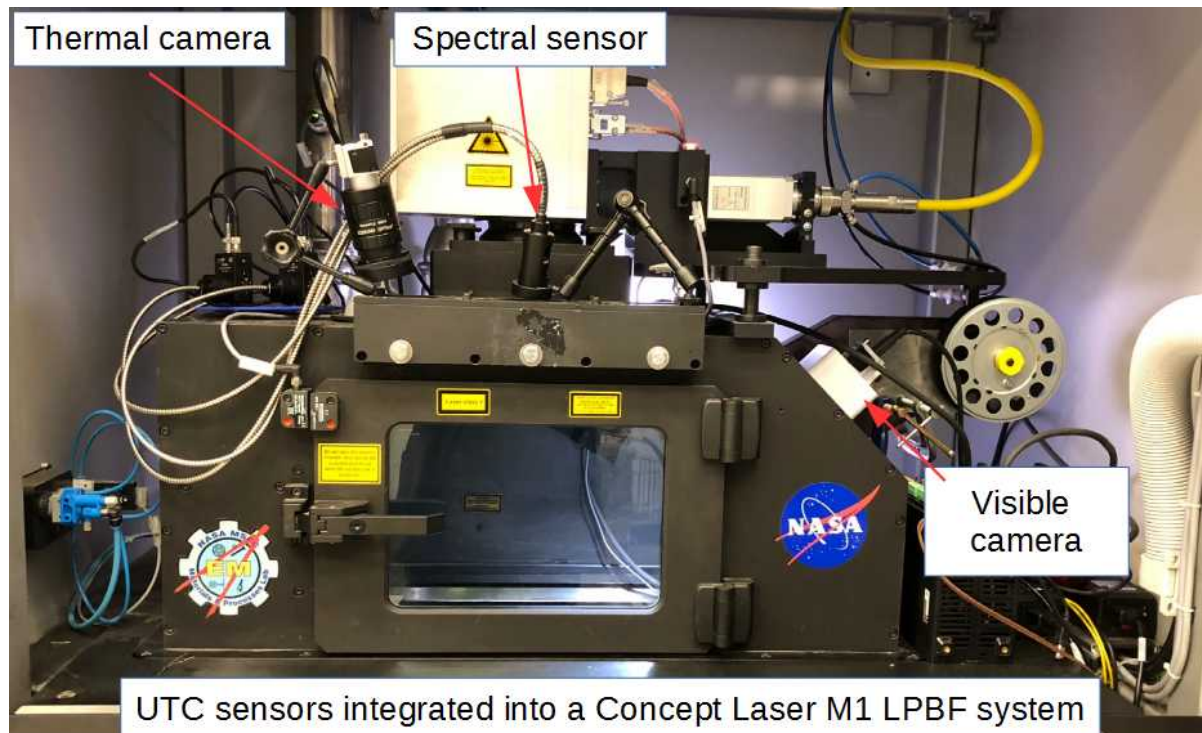


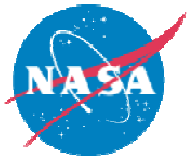
Langley's OPENSLM system, under construction



AMSENSE installed at MSFC

- Corroborating AMSENSE data is also being collected on builds on the Concept Laser M1 system at Marshall Space Flight Center.
- UTC has installed a pre-production version of the sensor package on the M1 and is actively collecting data.
 - The pre-production version will be upgraded to full-production once new software is completed.





Time Series Pattern Mining

Using data science to identify events in groups of spectra

Approach:

- Transform raw spectra data into a time series model capturing all features
- Clustering and pattern mining find significant events
- Identified patterns can train other machine learning tools

Software:

- R for conversion of proprietary spectra files and pre-processing
- MATLAB for data transforms, clustering, and pattern mining

Methodology:

- Spectra files are converted into a time series model
- Time series represents wavelength and count
- Filtering and peak identification reduce noise and isolate key events
- Clustering can be applied to group similar events and identify patterns
- Patterns can train additional machine learning methods for detection of undesirable events

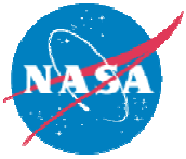
Results

- Robust method that performs well with raw data
- Able to identify two events in a subset of the “keyhole” spectra

Challenges

- Ground truth needed to determine if events are significant
- Adapted from other domains*; will require validation

*Methodology is based on techniques to identify biomarkers in mass spectrometry data; see *Gullo, F., Ponti, G., Tagarelli, A., Tradigo, G. and Veltri, P., 2012. A time series approach for clustering mass spectrometry data. Journal of Computational Science, 3(5), pp.344-355.*



Observations and Recommendations for Effective Machine Learning: *Incorporate Labels as Data is Collected*

Effective data science and machine learning models require SME-provided labels within the data itself. Labels can be thought of as the dependent variable that accompanies the various independent variables (also referred to as “features”) in a data set. Categorical labels (e.g. “*optimal*”, “*keyhole*”, or “*lack of fusion*”) can allow for more accurate classification, while binary labels (e.g. “*defect*” vs. “*non-defect*”) can be used with many different statistical and machine learning methods to produce more transparent results. Continuous measures can also be used, taking the role of a “target” label for predictive models. For images, a “ground truth” version that accurately captures each class must be provided.

Observation: *Lack of labels within numeric data*

The data used in this assessment was grouped by filename, but there were no labels within a given data set. For example, the spectra data did not contain sufficient information to determine if detected events were significant.

Recommendation

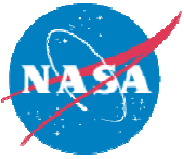
Future data sets should include a distinct label that identifies the category or state of each observation.

Observation: *Lack of ground truth for image data*

Images used in the assessment did not have an accompanying ground truth version. For example, the CT scans were grouped by a non-expert based on the presence of darker pixels, but bias could be introduced.

Recommendation

In order to accurately train and test machine learning models, a representative ground truth image must be provided.



Current Efforts

- SLM Builds (right)
 - AMSENSE data (hundreds of MBs)
 - OPENSIM system with forced defects
 - CT scanning scheduled
- MSFC Recyclability Study
 - AMSENSE data (>12 TBs)
 - Correlation with post build analysis
- Participants
 - John Middendorf (UTC, Dayton OH)
 - Karen Taminger (NASA Langley AMPB)
 - Andy Ramlachan (NASA Langley OCIO)
 - Jeremy Yagle (NASA Langley OCIO)
 - Bill Seufzer (NASA Langley AMPB)

