Producing Synthetic CT Imagery to Train 3D V-Net Segmentation Models

Thomas Pasfield
pasfielt@my.erau.edu

Embry-Riddle Aeronautical University,
Daytona Beach, FL

Motivation

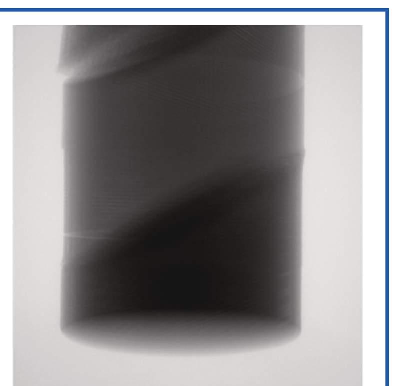
- While working on a previous 3-D Printing CT Analysis project [1], segmentation became the largest hurdle to overcome.
- Existing CT segmentation models focus on organic samples, not industrial samples.
- Industrial samples have more prior information, possibly allowing for easier bespoke segmentation model creation.
- Machine Learning (ML) model training requires training and test data, which should be able to be generated from the same data as the real print itself.

Objectives

- Develop an approach to parsing the necessary G-code for simulation.
- Develop a method to render the G-code in 2-D and 3-D space.
- Use real units and values in the render process. Generate labels for each voxel.
- Use the generated data to train a custom V-Net model to perform segmentation tasks.

Test Data

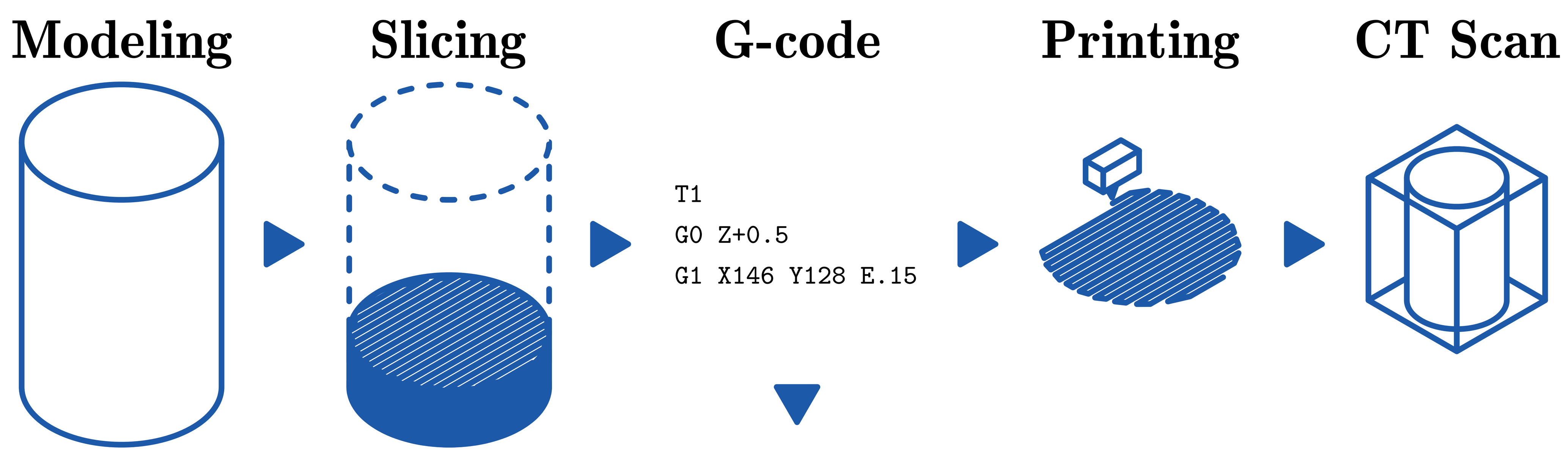
CT scan, model, and G-code data were provided by the Pacific Northwest National Laboratory for previous work. [1]



Future Work

- Fix the loss function for the V-Net; train V-Net on the ERAU Vega HPC Cluster.
- Improve CT simulation using the Radon transform reconstruction method from 2-D X-ray images.
- Add capability to simulate defects and physical constraints through modifying G-code.
- Explore and test other applications.

The Synthesis Framework



Simulation

Parse G-code

- Extract material, line widths, curves, and dimensions.
- Ignore skirts, supports, flush volume.
- Curves stored individually, separated by material and breaks.

Prepare Volume

- Use dimensions and user-provided scan resolution to create the volume.
- Populate volume with desired background values.

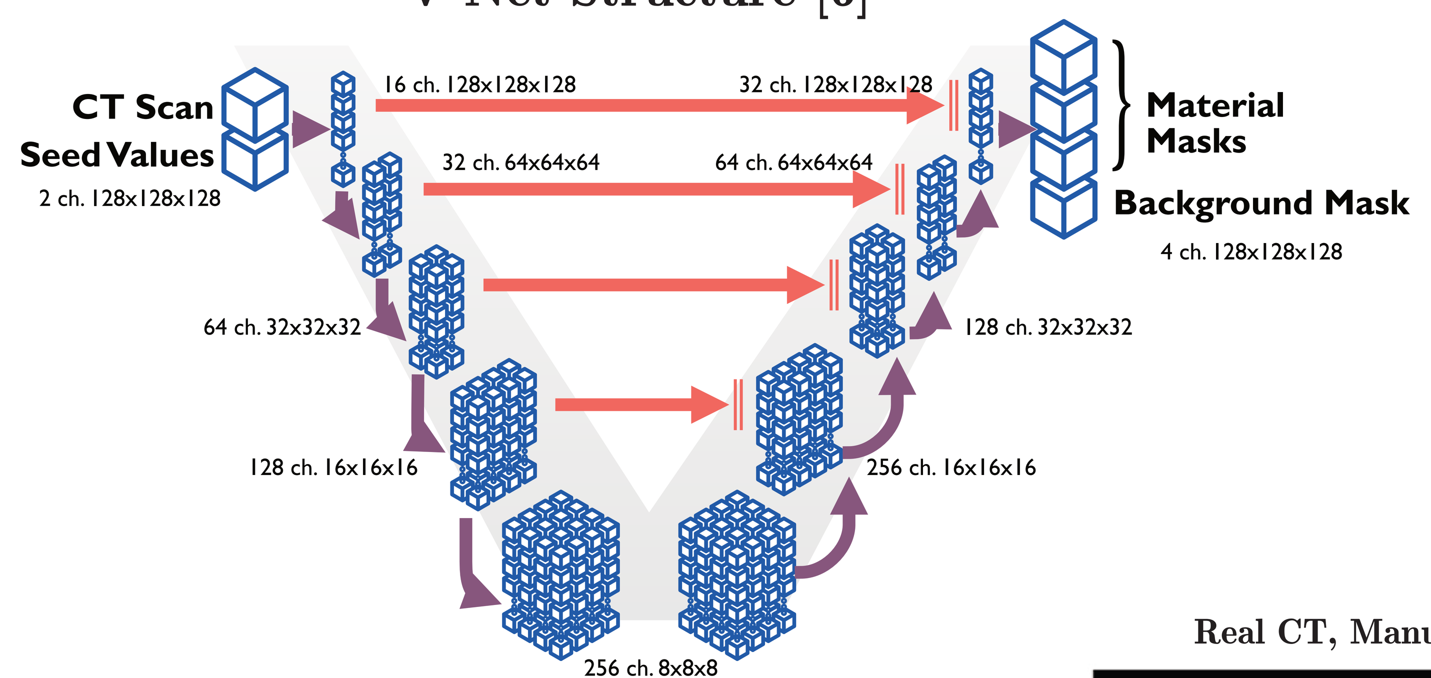
Trace Curves

- Break curves into individual line segments.
- Draw line segments in a discrete 3-D volume with a novel algorithm.
- Value determined by proximity to the line segment vector and the material.

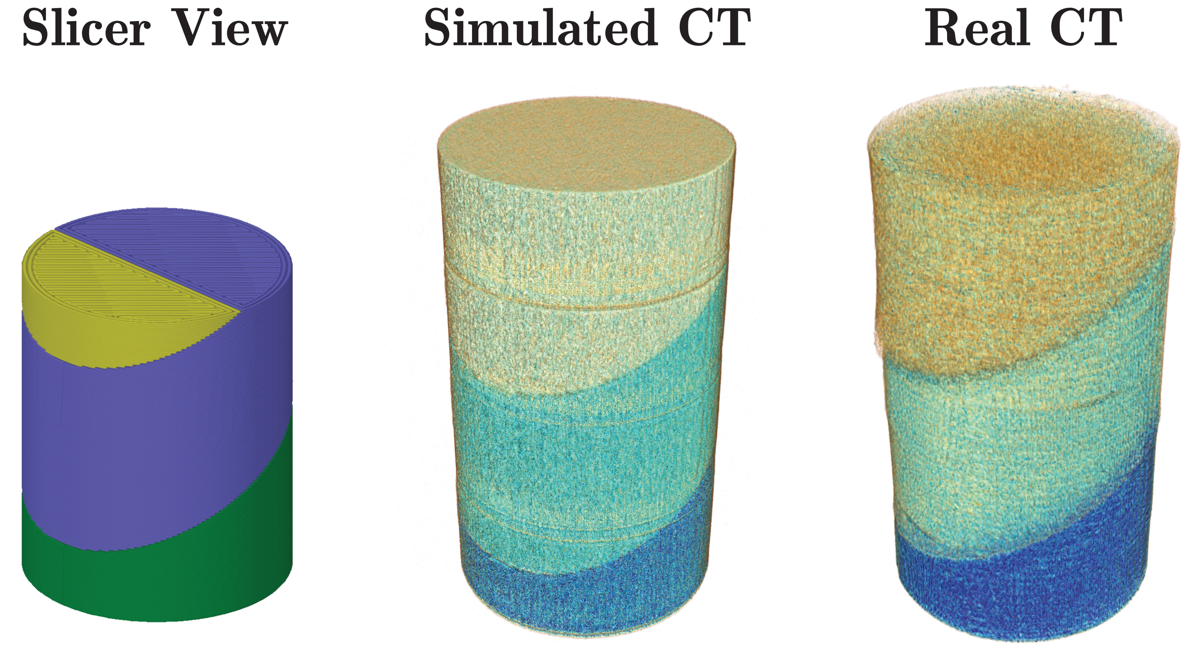
Save Volume

- Save the rendered scan into an HDF5 archive.
- Supports rendering and saving in sub-volumes.
- Save labels alongside value data.

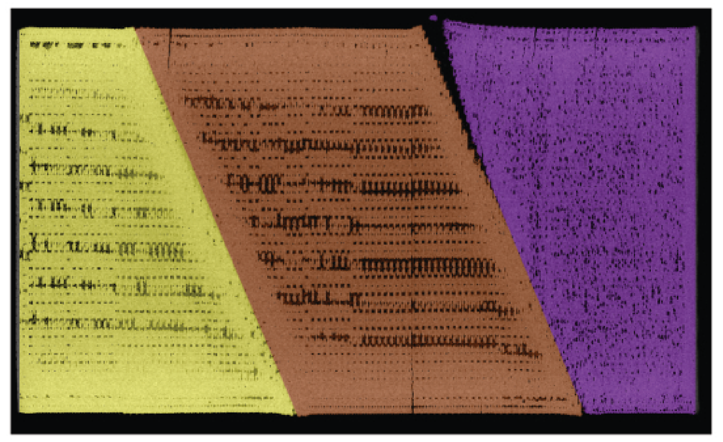
V-Net Structure [6]



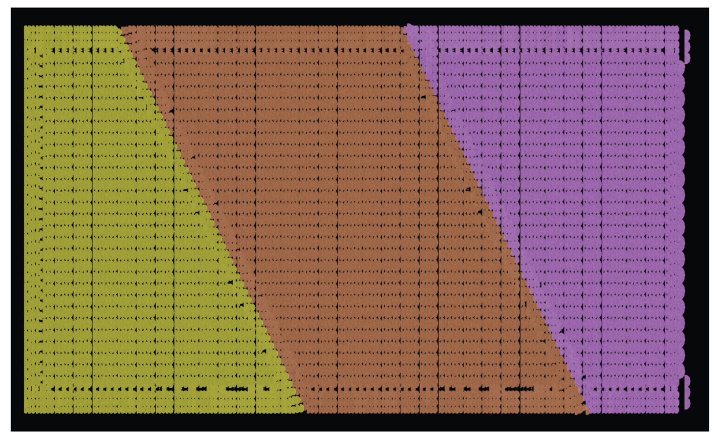
Slicer View | Simulated CT | Real CT



Real CT, Manual Segmentation



Simulated CT, Automated Segmentation



Applications

Error Quantification

- By comparing the ideal print as the expected outcome to the real scan, errors can be isolated and determined.
- Alignment of the scans is performed through image registration, often with a variation of SIFT/RANSAC. [2, 3]

Defect Detection

- Regions of large error can be used to find defects manually or enable more efficient blob detection methods.
- Simulating defects alongside ideal prints can serve as input for training ML detection models.
- Once the ML models are trained, simulation of each print is unnecessary if the model is sufficiently generalized.

Segmentation

- As this method outputs both simulated CT scans and labels for each voxel, it ideally serves to train ML segmentation models.
- Common CT segmentation models include 3-D U-Nets and V-nets, which are both similar. [4, 5, 6]
- Our example trains a V-Net on small regions of the simulated scan and randomly selects labeled points to use as seed values.
- When the model is deployed, the simulation labels may be usable as a seed values for segmenting the real data.

References

[1] T. Pasfield, I. Paraschos, K. Greene, R. Reynolds, D. Pereira, and J. Koscinsky, "Quantitative Analysis for Industrial Computed Tomography," presented at the Discovery Day - Daytona Beach, Embry-Riddle Aeronautical University, Daytona Beach, FL, Apr. 2024.

[2] B. Rister, M. A. Horowitz, and D. L. Rubin, "Volumetric Image Registration From Invariant Keypoints," IEEE Transactions on Image Processing, vol. 26, no. 10, pp. 4900–4910, Oct. 2017, doi: 10.1109/TIP.2017.2722689.

[3] P. Scovanner, S. Ali, and M. Shah, "A 3-dimensional sift descriptor and its application to action recognition," in Proceedings of the 15th ACM international conference on Multimedia, Augsburg Germany: ACM, Sep. 2007, pp. 357–360. doi: 10.1145/1291233.1291311.

[4] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," May 18, 2015, arXiv: arXiv:1505.04597. doi: 10.48550/arXiv.1505.04597.

[5] Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, "3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation," Jun. 21, 2016, arXiv: arXiv:1606.06650. doi: 10.48550/arXiv.1606.06650.

[6] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation," Jun. 15, 2016, arXiv: arXiv:1606.04797. doi: 10.48550/arXiv.1606.04797.

[7] L. Ibanez et al., InsightSoftwareConsortium/ITK: ITK 5.1 Release Candidate 1. (Dec. 23, 2019). Zenodo. doi: 10.5281/zenodo.3592082.