Spatiotemporal Data Analytics in 3D Printing Quality Prediction

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Presenation Outline

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- creates objects by laying down successive layers of material until the object is created

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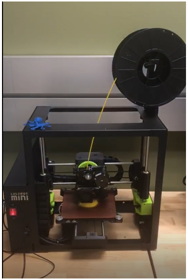
Benefits

• can directly build geometrically complex products with computer control
• less material and lower cost than traditional manufacturing methods



Problem Description

An optimization bottleneck

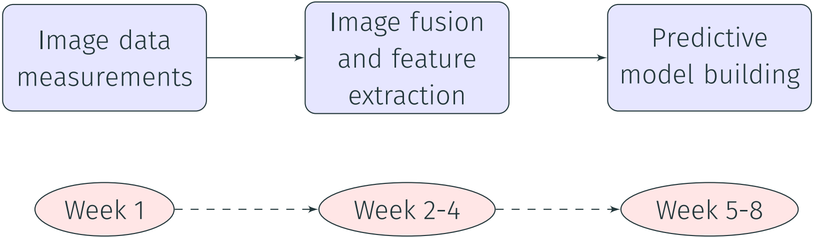
Material solidification in the printing process yields geometric shape deviation.

Traditionally, this problem is solved by manual inspection - works but **inefficient**.

Objectives

- Develop methods to extract spatiotemporal patterns from the measurement images to characterize printed parts quality
- Build a predictive model for part quality given process parameters

Project Timeline



Preliminary Work

- Image data measurements.

Use Keyence VR-3000 Wide-Area 3D Measurement system to measure the parameters from the surfaces of the 3D-printing object.

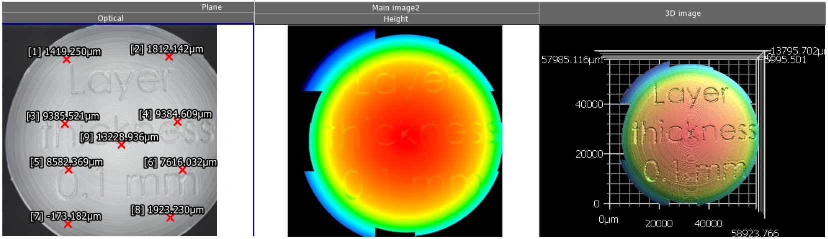


Figure 1: Measurement of point height of a dome object of layer thickness 0.1mm

Feature Extraction

The core question: how do we measure quality?

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Disadvantage: the features might be incomprehensive

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Advantage: comprehensiveness
Disadvantage: not really interpretable

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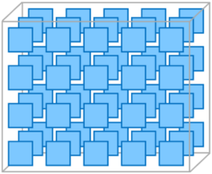

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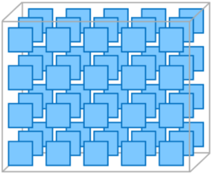

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- **Tensor Decomposition**: any scheme for expressing a tensor as a sequence of elementary operations acting on other, often simpler tensors.

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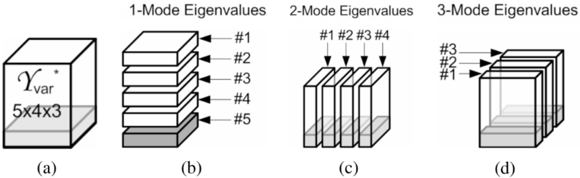
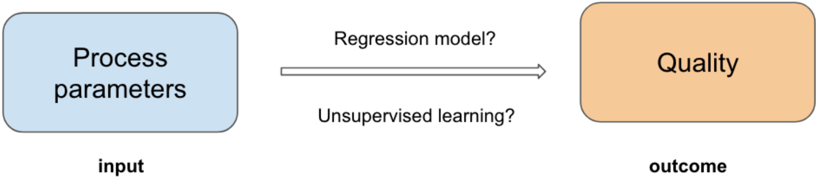
  Limitation: fails to take into account the spatial correlation of the image pixels within a localized neighborhood.
- MPCA: a multilinear algorithm performing dimensional reduction in all tensor modes seeking those bases in each mode that allow projected tensors to capture most of the variation present in the original tensors.



Visual illustration of (a) total scatter tensor, (b) 1-mode eigenvalues, (c) 2-mode eigenvalues, and (d) 3-mode eigenvalues.

Predictive Model



Potential Challenges

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References

- MPCA: Multilinear Principal Component Analysis of Tensor Objects
  `https://ieeexplore.ieee.org/document/4359192/`
- Image Fusion Using Tensor Decomposition and Coefficient Combining Scheme
  `http://www.ijettjournal.org/volume-15/number-9/IJETT-V15P286.pdf`