Spatiotemporal Data Analytics in 3D Printing
Quality Prediction

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Presentation Outline

- About 3D Printing
- Motivation
- Timeline and Methodologies
- Potential Challenges
- References
How does it work?

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

Benefits

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

Image data measurements → Image fusion and feature extraction → Predictive model building

Week 1 → Week 2-4 → Week 5-8

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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
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Disadvantage: the features might be incomprehensive
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**Advantage:** comprehensiveness

**Disadvantage:** not really interpretable
Tensor decomposition

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![Tensor Diagram](image)

**Figure 2**: rank 3 tensor

- **Tensor Decomposition**: any scheme for expressing a tensor as a sequence of elementary operations acting on other, often simpler tensors.
Multilinear Principal Component Analysis (MPCA)

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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

Process parameters → Regression model? → Quality

input → Unsupervised learning? → outcome

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Potential Challenges

- Unique sample, not many references to compare
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• Unique sample, not many references to compare solution: Create data from simulation.
References

- MPCA: Multilinear Principal Component Analysis of Tensor Objects

- Image Fusion Using Tensor Decomposition and Coefficient Combining Scheme