Spatiotemporal Data Analytics in 3D Printing Quality Prediction

Alex Xiaotong Gui, Pomona College
Xinru Liu, Wheaton College
June 4, 2018

Mentor: Dr. Weihong Grace Guo
DIMACS
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
3D Printing

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
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

1. Image data measurements
2. Image fusion and feature extraction
3. Predictive model building

Week 1

Week 2-4

Week 5-8
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

---

Alex Xiaotong Gui, Pomona College Xinru Liu, Wheaton College  
Mentor: Dr. Weihong Grace Guo  
DIMACS
The core question: how do we measure quality?
The core question: how do we measure quality?

Method 1: Build a geospatial model based on physical properties
Potential features: material texture, roughness, gradients
The core question: how do we measure quality?

Method 1: Build a geospatial model based on physical properties
Potential features: material texture, roughness, gradients

Advantage: interpretability
The core question: how do we measure quality?

Method 1: Build a geospatial model based on physical properties

Potential features: material texture, roughness, gradients

Advantage: interpretability

Disadvantage: the features might be incomprehensive
Method 2: Data driven approaches

Our data: for each sample, discretize the image domain (for example $100 \times 100$) and extract the average height of each area. For $n$ samples, we will have a $100 \times 100 \times n$ tensor of heights data. We will then deploy tensor decomposition technique to extract features of lower dimension.

Advantage: comprehensiveness
Disadvantage: not really interpretable
Method 2: Data driven approaches

Our data: for each sample, discretize the image domain (for example $100 \times 100$) and extract the average height of each area.
Method 2: Data driven approaches

Our data: for each sample, discretize the image domain (for example $100 \times 100$) and extract the average height of each area. For $n$ samples, we will have a $100 \times 100 \times n$ tensor of heights data.
Method 2: Data driven approaches

Our data: for each sample, discretize the image domain (for example $100 \times 100$) and extract the average height of each area. For $n$ samples, we will have a $100 \times 100 \times n$ tensor of heights data.

We will then deploy tensor decomposition technique to extract features of lower dimension.
Method 2: Data driven approaches

Our data: for each sample, discretize the image domain (for example $100 \times 100$) and extract the average height of each area. For $n$ samples, we will have a $100 \times 100 \times n$ tensor of heights data.

We will then deploy tensor decomposition technique to extract features of lower dimension.

Advantage: comprehensiveness
Method 2: Data driven approaches

Our data: for each sample, discretize the image domain (for example $100 \times 100$) and extract the average height of each area. For n samples, we will have a $100 \times 100 \times n$ tensor of heights data.

We will then deploy tensor decomposition technique to extract features of lower dimension.

**Advantage:** comprehensiveness

**Disadvantage:** not really interpretable
Tensor decomposition

- **Tensors**: geometric objects that describe linear relations between geometric vectors, scalars, and other tensors. It generalizes matrices to higher dimensions.
• **Tensors**: geometric objects that describe linear relations between geometric vectors, scalars, and other tensors. It generalizes matrices to higher dimensions.

![Tensor Diagram](image)

**Figure 2**: rank 3 tensor
Tensor decomposition

- **Tensors**: geometric objects that describe linear relations between geometric vectors, scalars, and other tensors. It generalizes matrices to higher dimensions.
  
  e.g.

- **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)

- PCA: Unsupervised linear technique for dimensionality reduction.
Multilinear Principal Component Analysis (MPCA)

- PCA: Unsupervised linear technique for dimensionality reduction.
  **Limitation:** fails to take into account the spatial correlation of the image pixels within a localized neighborhood.
Multilinear Principal Component Analysis (MPCA)

- **PCA**: Unsupervised linear technique for dimensionality reduction. **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**
  - Input

- **Regression model?**

- **Unsupervised learning?**

- **Quality**
  - Outcome
Potential Challenges

- Unique sample, not many references to compare
Potential Challenges

- 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