Multimodal Data Fusion in 3D Printing Quality Prediction

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DIMACS

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Motivation

- Quality characterization is traditionally done by manual inspection.
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- Can we use data from multiple sources to characterize quality more efficiently and effectively?

What determines the quality of the printed parts?

Figure: Printed dome objects
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- Can we use data from multiple sources to characterize quality more efficiently and effectively?
- What determines the quality of the printed parts?

**Figure**: Printed dome objects
Objectives

- Develop methods to extract patterns from measurement data to characterize printed parts quality
- Build a predictive model for part quality given features and process parameters
Research Roadmap

- Data Collection
- Feature Extraction
- Developing Quality Metrics
- Classification and Regression
Stage 1: Data Collection

- Dome shapes only
- Two data sources
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- Two data sources
  - Printing parameters
    - speed: 20/40/60 (mm/s)
    - fill: 20/40/60/100 (%)
    - thickness: 0.1/0.2 (mm)
Stage 1: Data Collection

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Our Data

- From the image measurements
  - point height matrix
  - profiles
  - surface roughness
Stage 2: Data-driven Feature Extraction

Image data

- 1520 x 1628 height data points
- 20 observations
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Image data
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Dimensionality Reduction
- Principal Component Analysis (PCA)
- Uncorrelated Multi-linear Principal Component Analysis (MPCA)
Principal Component Analysis Explanation

Model Intuition

- High dimensional data $\rightarrow$ a new set of uncorrelated features (principal components)
- The first principal component direction of the data is that along which the observations vary the most.
- The principal components are ordered by decreasing variance

Figure: An example from Introduction to Statistical Learning
PCA Theory Illustration

Vectorizing matrix as vector with length $1520 \times 1628 = 2474560$

Figure: PCA Graphical Illustration. By Digital image.
Reconstruction

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of variance</td>
<td>0.44</td>
<td>0.306</td>
<td>0.08</td>
<td>0.059</td>
<td>...</td>
</tr>
</tbody>
</table>

![Reconstruction Images]

reconstruction with PC1

reconstruction with PC1 and PC2

reconstruction with PC1, PC2, and PC3

reconstruction with PC1, PC2, PC3, and PC4
Limitation of PCA

- Requires the reshaping of tensors into high dimensional vectors
- Fails to take into account the spatial correlation of height data within a localized neighborhood.
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**MPCA**
- Can operate on tensors directly
- Generates uncorrelated features in a similar fashion to PCA
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MPCA

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Figure: From top left to down right: illustration of the first four MPCs
Stage 3: Developing Quality Metrics

Part I: Geometric Shape Deviation

- We took six profile measurements of the 20 samples
- Designated fill 20, speed 20, height 0.1mm dome as the reference (standard sample)
- The goal is to quantify the geometric deviation of each sample from the reference
Challenge

The real data is imperfect

- The curves are not aligned
- Requires a consistent interpolation
- Manual adjustment is inefficient

Figure: The reference sample and 20.40.0.1 before alignment
Dynamic Time Warping

- Widely used in speech recognition, computer vision and time series
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- The goal is to find a matching between two curves of length \( m \) and \( n \) such that the total distance between the matched points is minimized

Figure: An example of dynamic programming solution from Keogh, 2001
Dynamic Time Warping

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- Solution uses dynamic programming-run time is \( O(mn) \)
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**Figure:** An example of dynamic programming solution from Keogh, 2001
Figure: Using dtw to align our data
Quantify Deviation

**Step 1:** Use Locally Weighted Scatterplot Smoothing (LOESS) Regression to fit the curve of reference profile.

We define profile residual as:

\[ e = \sum_{n=1}^{N} (\hat{Z} - Z)^2 \]

where \( N \) is the length of the profile vector.
Quantify Deviation

**Step 1:** Use Locally Weighted Scatterplot Smoothing (LOESS) Regression to fit the curve of reference profile

**Step 2:** Predict the height coordinates ($Z$) of the other samples using the reference model fit. Let the prediction be $\hat{Z}$.
**Quantify Deviation**

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We define profile residual as

$$
e = \frac{\sum_{n=1}^{N} (\hat{Z} - Z)^2}{N}
$$

where $N$ is the length of the profile vector
Part II: Surface Roughness

Developed Interfacial Area Ratio
This parameter, $S_{dr}$, is expressed as the percentage of the definition area’s additional surface area contributed by the texture as compared to the planar definition area.

Figure: Roughness Illustration
Label the samples

Objective: use profile residual and roughness data to cluster our samples into two classes, "good quality" and "bad quality".
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k-means clustering

Partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.

\[ W(C_k) = \sum_{x_i \in C_k} (x_i - \mu)^2 \]

where \( x_i \) is a data point belonging to the cluster \( C_k \), \( \mu \) is the mean value of the points assigned to the cluster \( C_k \).
Stage 4: Modeling - Classification

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Clustering between roughness and profile residual

- **Good**
- **Bad**
- **Good mean**
- **Bad mean**
Decision Tree
- Split data into train (n=14) and test (n=6)
- Run a decision tree algorithm on train set
Test accuracy: 66.7%
Important Variables: PC3, PC4

Figure: Decision tree with PCA components
Modeling - Classification with MPCA

Test accuracy: 83.3%
Important Variables: MPC2, MPC3, MPC4

Figure: Decision tree with MPCA components
Modeling - Multi Linear Regression (Profile residual)

Response variable: profile residual
Predictors: (M)PC1, (M)PC2, (M)PC3, (M)PC4, fill, speed, thickness

Table: Profile residual (PCA)

<table>
<thead>
<tr>
<th></th>
<th>PC2</th>
<th>PC3</th>
<th>fill</th>
<th>speed</th>
<th>thickness</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>-2.156e-07</td>
<td>-2.557e-07</td>
<td>4.326e-02</td>
<td>-2.633e-02</td>
<td>1.936e+01</td>
</tr>
<tr>
<td>P-value</td>
<td>0.08765</td>
<td>0.22012</td>
<td><strong>0.00085</strong></td>
<td>0.08818</td>
<td><strong>0.00243</strong></td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.8332

Table: Profile residual (UMPCA)

<table>
<thead>
<tr>
<th></th>
<th>MPC1</th>
<th>MPC1²</th>
<th>MPC2</th>
<th>fill</th>
<th>speed</th>
<th>thickness</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>-4.071e-01</td>
<td>-1.298e+00</td>
<td>-3.235e-07</td>
<td>3.947e-02</td>
<td>-2.550e-02</td>
<td>2.111e+01</td>
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<tr>
<td>P-value</td>
<td>0.63626</td>
<td>0.13063</td>
<td>0.09074</td>
<td><strong>0.00205</strong></td>
<td>0.12527</td>
<td><strong>0.00152</strong></td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.8747
Modeling: Multi Linear Regression (Roughness)

Response variable: Roughness

Table: Roughness (PCA)

<table>
<thead>
<tr>
<th></th>
<th>PC3</th>
<th>PC4</th>
<th>fill</th>
<th>speed</th>
<th>thickness</th>
<th>fill*thickness</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>2.976e-08</td>
<td>-7.399e-08</td>
<td>5.516e-03</td>
<td>-2.298e-03</td>
<td>2.203e+00</td>
<td>-4.163e-02</td>
</tr>
<tr>
<td>P-value</td>
<td>0.2151</td>
<td>0.0650</td>
<td>0.0530</td>
<td>0.1498</td>
<td>0.0371</td>
<td>0.0202</td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.4587

Table: Roughness (UMPCA)

<table>
<thead>
<tr>
<th></th>
<th>MPC3</th>
<th>MPC4</th>
<th>fill</th>
<th>speed</th>
<th>thickness</th>
<th>fill*thickness</th>
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</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>1.544e-07</td>
<td>3.122e-07</td>
<td>5.291e-03</td>
<td>-2.048e-03</td>
<td>2.332e+00</td>
<td>-3.893e-02</td>
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<tr>
<td>P-value</td>
<td>0.0391</td>
<td>0.1385</td>
<td>0.0536</td>
<td>0.1498</td>
<td>0.0210</td>
<td>0.0187</td>
</tr>
</tbody>
</table>

Adjusted R-squared: 0.5402
Insights

- (M)PC2 is relatively more significant in the model predicting the profile residuals.

- (M)PC3 and (M)PC4 are relatively more significant in the model predicting the surface roughness.

- Fill and layer thickness are significant to predict the quality.

- The effect of fill on quality is different for different values of layer thickness.
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- The effect of fill on quality is different for different values of layer thickness.
Using principal components instead of geometric measurements can reduce human error.
More efficient to evaluate the quality of the 3D printing object.
Future work

- Imputation
- More precise curve matching
- Better tuned models
- More samples $\rightarrow$ more power!
Keogh, Eamonn J and Pazzani, Michael J (2001)
Derivative Dynamic Time Warping
*2001 SIAM International Conference on Data Mining*

James, Gareth and Witten, Daniela and Hastie, Trevor and Tibshirani, Robert (2014)
An Introduction to Statistical Learning: With Applications in R

KH. Lu and K. N. Plataniotis and A. N. Venetsanopoulos (2009)
Uncorrelated Multilinear Principal Component Analysis for Unsupervised Multilinear Subspace Learning
*IEEE Transactions on Neural Networks vol.20, no.11, 2009, pp. 1820-1836*
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