Multimodal Data Fusion in 3D Printing Quality Prediction

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DIMACS

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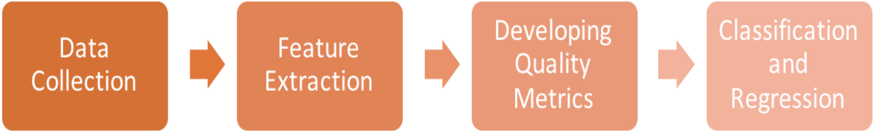
Figure: Printed dome objects

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



Stage 1: Data Collection

- Dome shapes only
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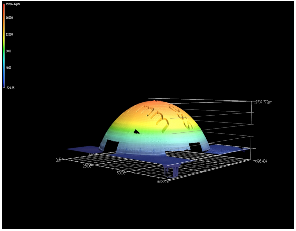
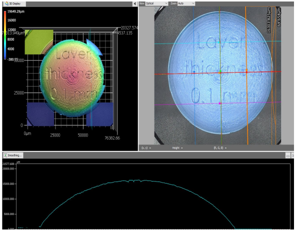
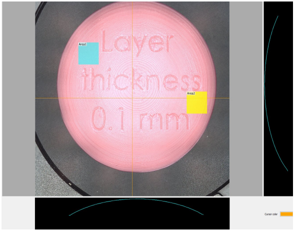
Our Data

- From the image measurements
  - point height matrix
  - profiles
  - surface roughness







Stage 2: Data-driven Feature Extraction

Image data

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- 20 observations

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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

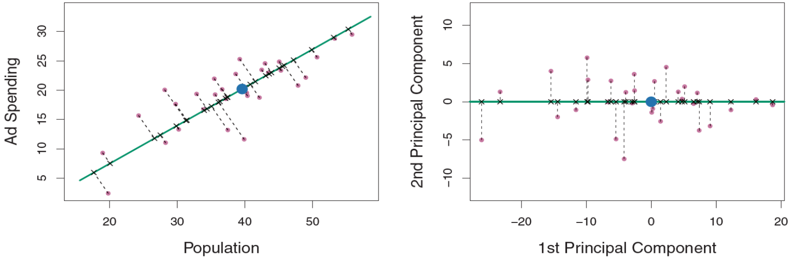


Figure: An example from Introduction to Statistical Learning

PCA Theory Illustration

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

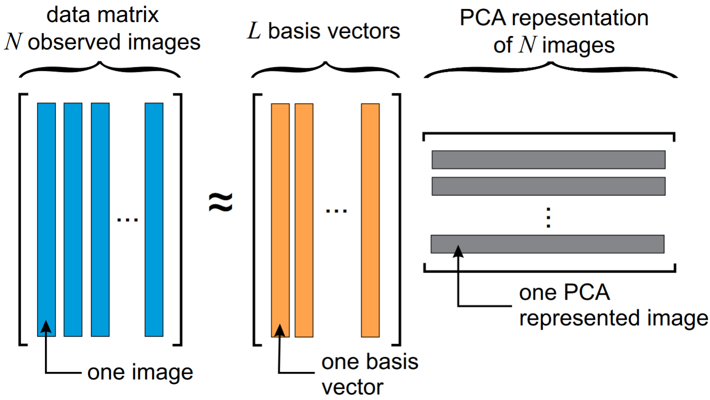
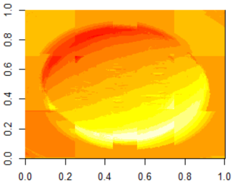
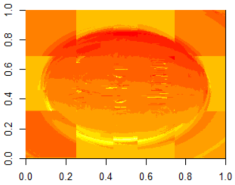


Figure: PCA Graphical Illustration. *By Digital image. Http://people.ciirc.cvut.cz/ hlavac/TeachPresEn/11ImageProc/15PCA.pdf. N.p., n.d. Web.*

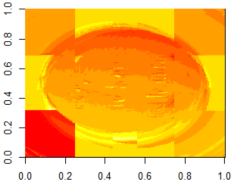
	PC1	PC2	PC3	PC4	...
Proportion of variance	0.44	0.306	0.08	0.059	...



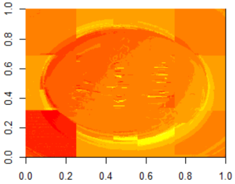
reconstruction with PC1



reconstruction with PC1 and PC2



reconstruction with PC1, PC2, and PC3



reconstruction with PC1, PC2, PC3, and PC4

Multi-linear Principal Component Analysis

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 Reconstruction

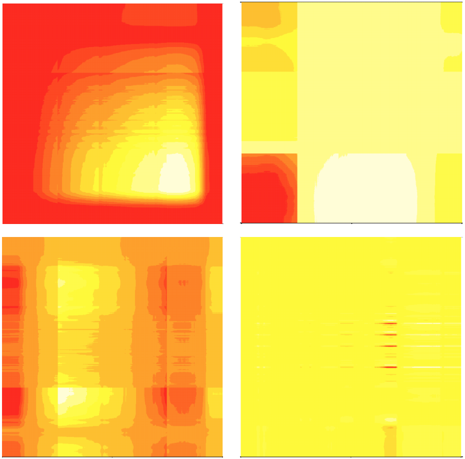

Figure: From top left to down right: illustration of the first four MPCs

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

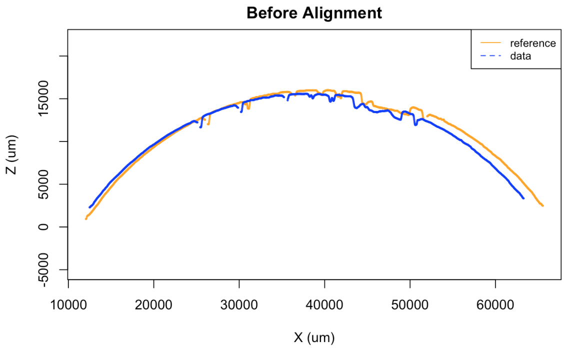

Figure: The reference sample and 20_40_0.1 before alignment

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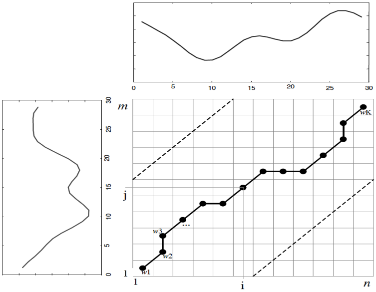

Figure: An example of dynamic programming solution from Keogh, 2001

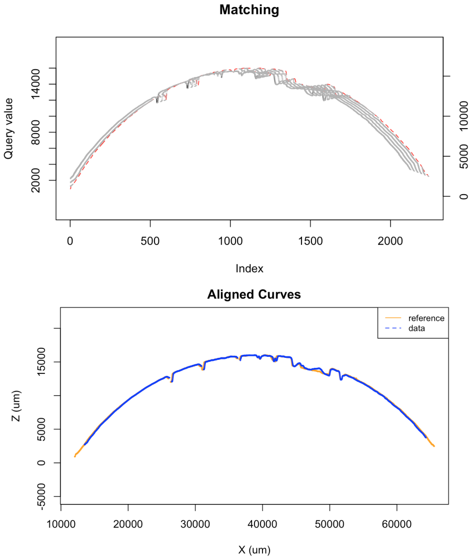

Figure: Using dtw to align our data

Quantify Deviation

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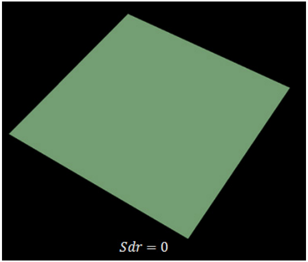
We define profile residual as

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

where N is the length of the profile vector

Developed Interfacial Area Ratio

This parameter, *Sdr*, is expressed as the percentage of the definition area's additional surface area contributed by the texture as compared to the planar definition area.



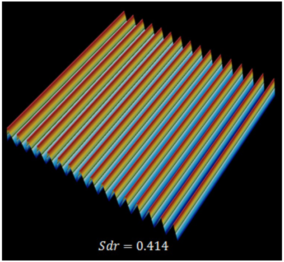


Figure: Roughness Illustration

Stage 4: Modeling - Classification

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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.

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

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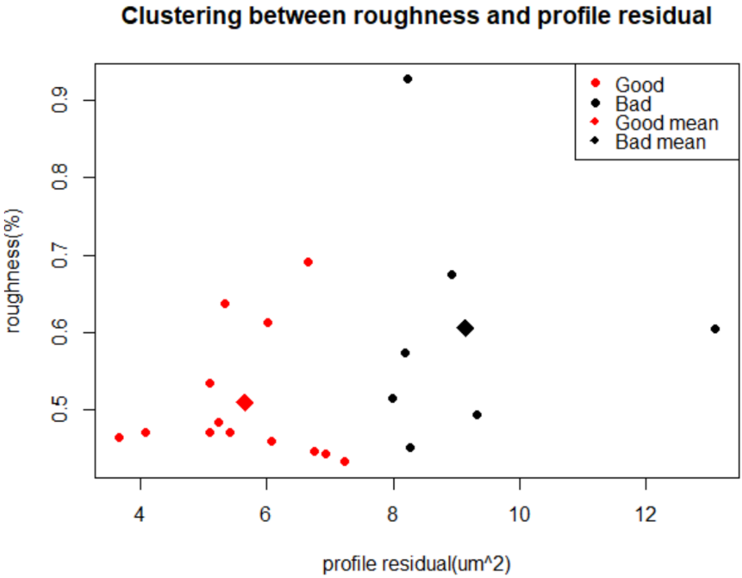
Clustering


Clustering between roughness and profile residual
Good
Bad
Good mean
Bad mean
roughness(%)
0.5
0.6
0.7
0.8
0.9
4
6
8
10
12
profile residual(um^2)

Modeling - Classification with PCA

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

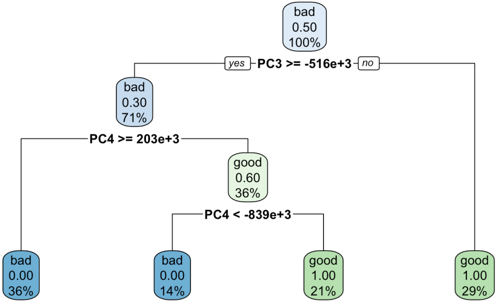


Figure: Decision tree with PCA components

Modeling - Classification with MPCA

Test accuracy: 83.3%

Important Variables: MPC2, MPC3, MPC4

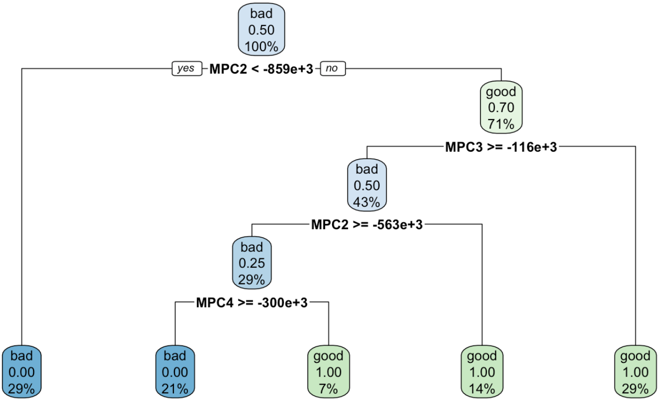


Figure: Decision tree with MPCA components

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)

	PC2	PC3	fill	speed	thickness
coefficient	-2.156e-07	-2.557e-07	4.326e-02	-2.633e-02	1.936e+01
P-value	0.08765	0.22012	**0.00085**	0.08818	**0.00243**

Adjusted R-squared: 0.8332

Table: Profile residual(UMPCA)

	MPC1	$MPC1^2$	MPC2	fill	speed	thickness
coefficient	-4.071e-01	-1.298e+00	-3.235e-07	3.947e-02	-2.550e-02	2.111e+01
P-value	0.63626	0.13063	0.09074	**0.00205**	0.12527	**0.00152**

Adjusted R-squared: 0.8747

Modeling: Multi Linear Regression (Roughness)

Response variable: Roughness

Table: Roughness (PCA)

	PC3	PC4	fill	speed	thickness	fill*thickness
coefficient	2.976e-08	-7.399e-08	5.516e-03	-2.298e-03	2.203e+00	-4.163e-02
P-value	0.2151	0.0650	**0.0530**	0.1498	**0.0371**	**0.0202**

Adjusted R-squared: 0.4587

Table: Roughness (UMPCA)

	MPC3	MPC4	fill	speed	thickness	fill*thickness
coefficient	1.544e-07	3.122e-07	5.291e-03	-2.048e-03	2.332e+00	-3.893e-02
P-value	**0.0391**	0.1385	0.0536	0.1498	**0.0210**	**0.0187**

Adjusted R-squared: 0.5402

Insights

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Impact

- 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!

References

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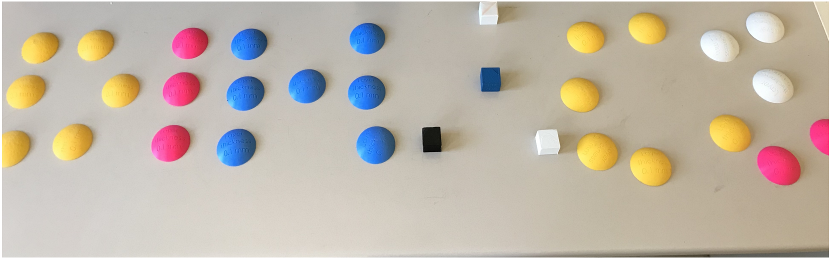

Figure: DIMACS in 3D Printed Parts