Geometric Shape Deformation Control for Additive Manufacturing

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Shape Deformation Control in Cybermanufacturing Systems

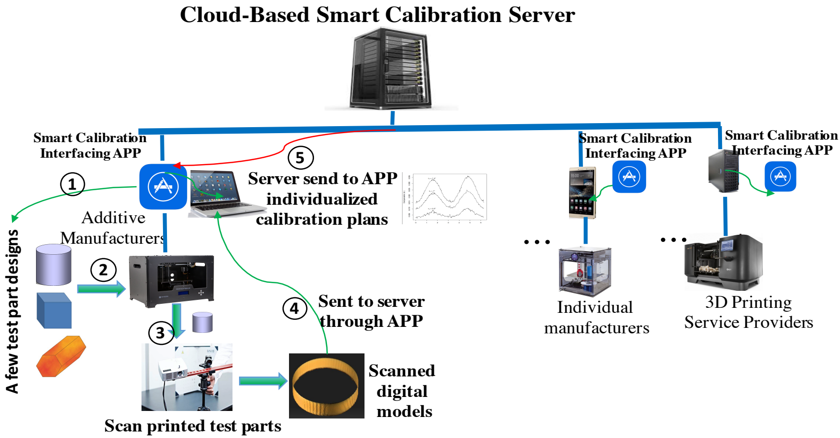


Figure: Cyberphysical Additive Manufacturing Systems

Outline

- Motivation: *How to provide cloud-based accuracy control service under cybermanufacturing environments*?
- Shape accuracy control for additive manufacturing (AM):
  - **Forward problem**: prescriptive modeling using limited training shapes [Huang et al., 2015, Huang et al., 2014b, Sabbaghi et al., 2014, Luan and Huang, 2016, Jin et al., 2016, Huang, 2016]
  - **Inverse problem**: optimal compensation of shape deformation [Huang, 2016]
  - **Learning problem**: Bayesian learning for improved prediction [Sabbaghi et al., 2015, Sabbaghi et al., 2016]
  - **Transfer Learning problem**: model transfer from one process to another [Sabbaghi and Huang, 2016]
- Summary and on-going work

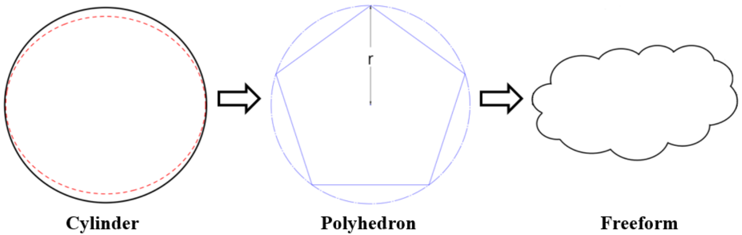
Challenges: One-of-a-Kind Mfg vs. Mass Production

- Huge varieties and shape complexity
- Heterogeneous fabrication conditions with variations
- Low-volume production, in particular, one-of-a-kind manufacturing
- Disparate data generated under different process conditions

The paradigm-shift due to one-of-a-kind manufacturing introduces the need for new quality control methodologies

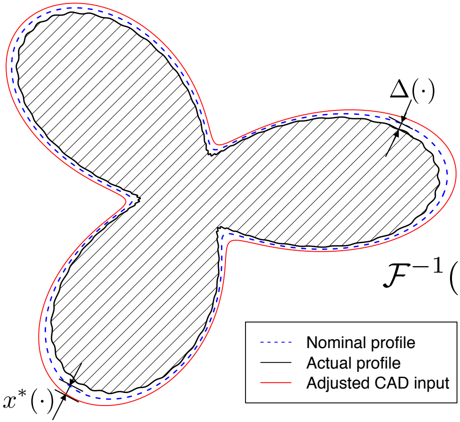
Focus of This Talk

1. How to quickly calibrate AM processes based a limited number of trial shapes (a few cylinders and polyhedrons)



2. How to quickly transfer the model learned under one condition to another?

Intuitive Calibration Strategy to Reduce Shape Deformation Through Compensation



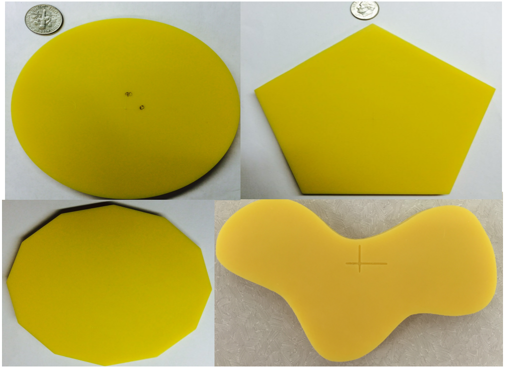
Forward

$$\Delta(\cdot) \Longrightarrow \mathcal{F}(\cdot)$$

Inverse

$$\mathcal{F}^{-1}(\cdot) = x^*(\cdot) \Longleftarrow \mathcal{F}(\cdot)$$

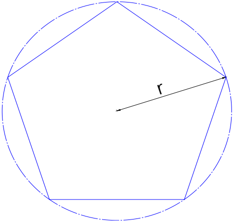
1. Prescriptive Modeling for Shape Deformation Prediction: Forward Problem



[Huang et al., 2015, Sabbaghi et al., 2014, Huang et al., 2014b, Luan and Huang, 2016]

A New Cookie-Cutter Prescriptive Modeling Framework

- A polygon can be viewed as being carved out from a circle, like cutting a cookie from a circular dough [Huang et al., 2014a, Huang et al., 2014b]:



- Cylindrical deformation and cookie-cutter are treated as separate basis functions or **model primitives**:

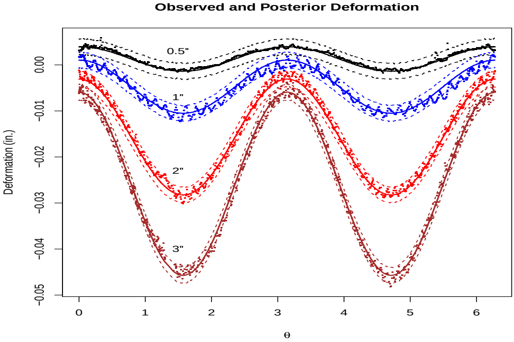
$$\underbrace{\Delta r(\theta, r_0(\theta))}_{\text{shape deformation}} = \underbrace{g_1(r_0(\theta))}_{\text{cylindrical basis func.}} + \underbrace{g_2(\theta, r_0(\theta))}_{\text{cookie-cutter func.}} + \varepsilon \quad (1)$$

Prescriptive Modeling: Cylindrical Basis $g_1(r_0(\theta))$

Simple harmonic term for $g_1(r_0(\theta))$ is sufficient. [Huang et al., 2015]

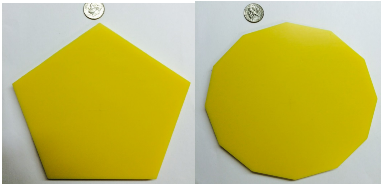
$$g_1(r_0(\theta)) = x_0 + \alpha(r_0 + x_0)^a + \beta(r_0 + x_0)^b \cos(2\theta)$$

Estimation through Hamiltonian Monte Carlo (HMC) [Neal, 2010]

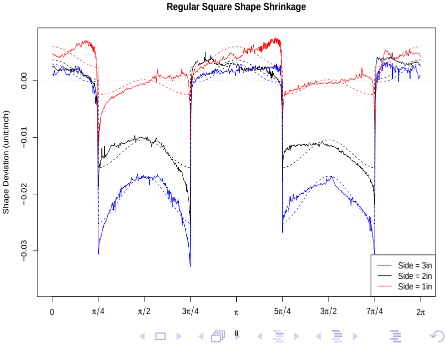


Prescriptive Modeling: Polyhedrons and Function $g_2(r_0(\theta))$

$$\Delta r(\theta, r_0(\theta)) = \overbrace{\beta_0 + \beta_1 cos(2\theta)}^{\text{cylindrical basis model } g_1(\cdot)} + \underbrace{\beta_2 sign[cos(n(\theta - \phi_0)/2)]}_{\text{cookie-cutter model } g_2(\theta, r(\theta))} + \varepsilon \quad (2)$$



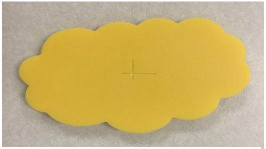
Polygon shape with n sides and circumcircle radius $r \Longrightarrow$ circle when $n = \infty$

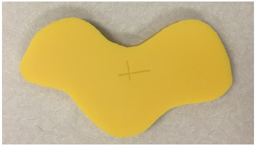


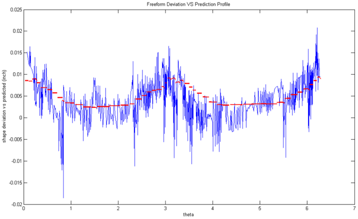
Prescriptive Modeling: Predicting Freeform Deformation

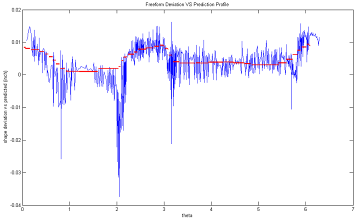
Generalized cookie-cutter model: [Luan and Huang, 2015, Luan and Huang, 2016]

$$\Delta r(\theta, r_0(\theta)) = \underbrace{g_1(\theta, r_i(\theta_i))}_{\text{arcs of circular sectors}} + \underbrace{g_2(\theta, r_i(\theta_i))}_{\text{edges of polygons}} + \varepsilon \qquad (3)$$



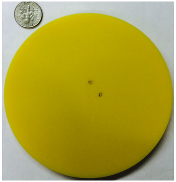


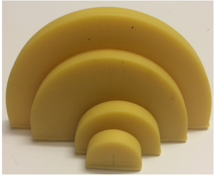


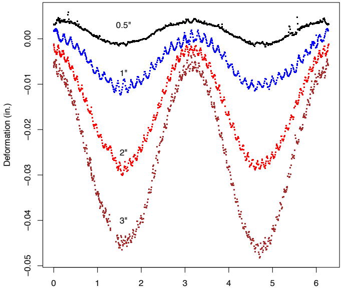


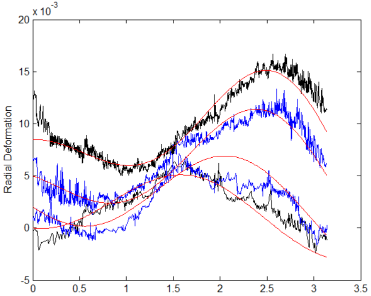
Extension to Out-of-Plane Freeform Deformation

Inter-layer bonding and accumulation effects along z direction:



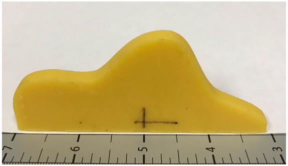


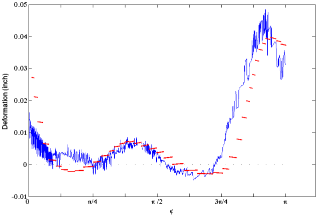


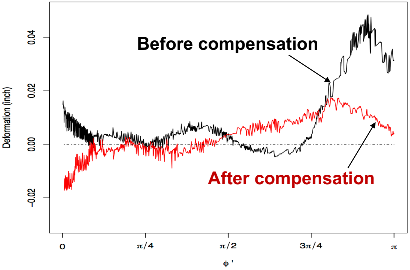


Extension to Out-of-Plane Freeform Deformation: Freeform

Validation: Prediction and compensation of out-of-plane deformation







2. Inverse Problem: Optimal Compensation of Shape Deformation [Huang et al., 2015, Huang, 2016]

Definition (Minimum Area Deviation (MAD) Criterion)

For a 2D shape deviating from its intended design model, the minimum area deviation (MAD) criterion is satisfied if the total absolute area change of the deformed shape is the smallest.

Theorem (Minimum-Area-Deviation Compensation)

The optimal compensation policy below satisfies MAD criterion.

$$x^*(\theta) = -\frac{f(\theta, r_0(\theta))}{1 + \bigtriangledown f(\theta, r_0(\theta))} \tag{4}$$

Theoretical Foundation: Minimum Volume Deviation (MVD) Criterion and Compensation

Theorem (Minimum Volume Deviation)

The optimal compensation policy or the optimal amount of compensation $x^*(\theta, \varphi)$ *for spatial shape deformation reduction is*

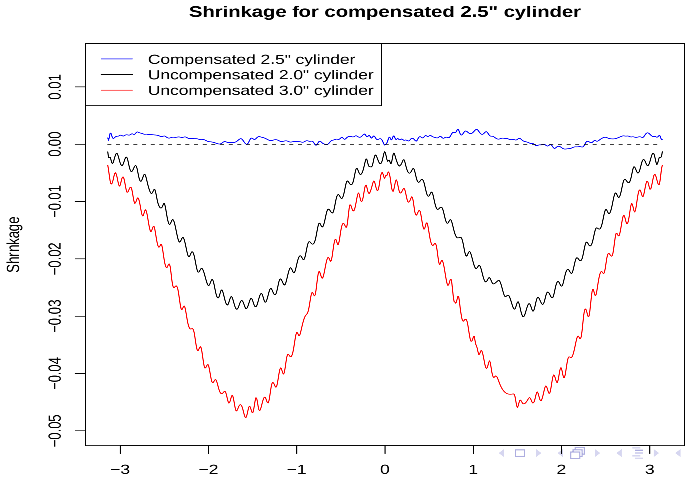
$$x^*(\theta, \varphi) = -\frac{f(\theta, \varphi, r_0(\theta, \varphi))}{1 + \triangledown f(\theta, \varphi, r_0(\theta, \varphi))} \tag{5}$$

which minimizes the volume deviation from its nominal shape, that is, it follows the minimum volume deviation (MVD) criterion.

Optimal Compensation of 2D Shape Deformation

Tested cylinder (90%), polyhedrons, and freeform shapes (>50%),

[Huang et al., 2015, Huang et al., 2014b, Luan and Huang, 2016]



3. Bayesian Learning from Small Samples of Disparate Data in AM – Learning Problem

Motivation: After fabricating a product (w/wo optimal compensation), how could we learn from the observed data for model improvement?

[Sabbaghi et al., 2015, Sabbaghi et al., 2016]

Bayesian learning of cookie-cutter model:

- Cookie-cutter modeling framework [Huang et al., 2014b], and

$$\Delta r(\theta, r_1(\cdot)) = g_1(\theta, r_0) + g_2(\theta, r_1(\cdot)) + \varepsilon_\theta$$

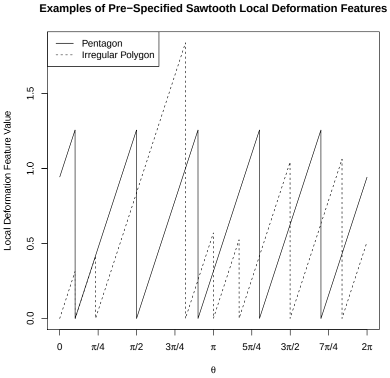
- Bayesian posterior predictive checks [Gelman et al., 1996; Gelman, 2003].

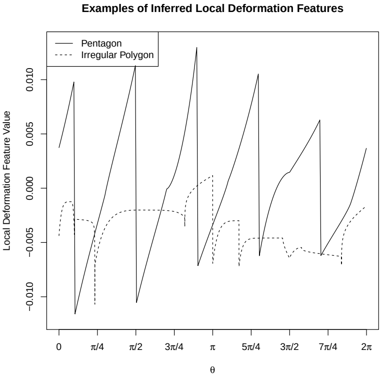
$$\Delta r(\theta, r_1(\cdot)) - g_1(\theta, r_0).$$

This discrepancy measure [Meng, 1994] can illuminate parsimonious specifications for g_2.

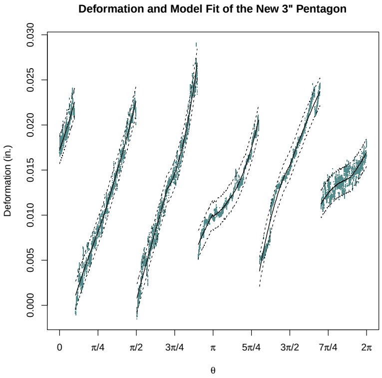
Learning Cookie-Cutter Model

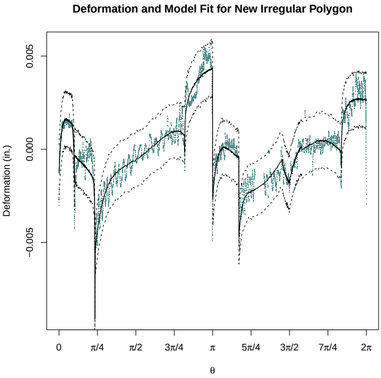
- Keep cylindrical basis g_1 and learn cookie-cutter function $g_2(\cdot)$
- Improved cookie-cutter model $g_2(\cdot)$ applicable to freeform shapes



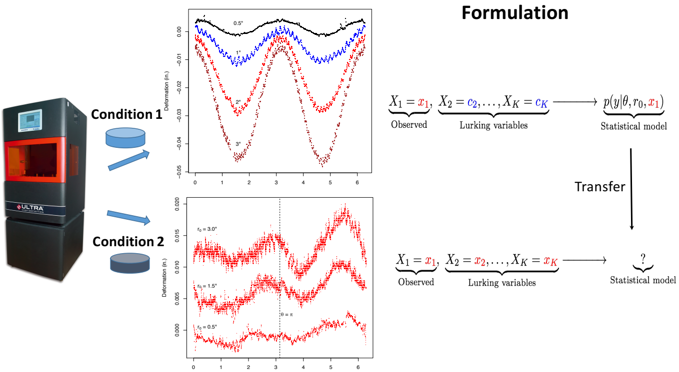


Improved Model Prediction





4. Model Transfer from One Condition to Another



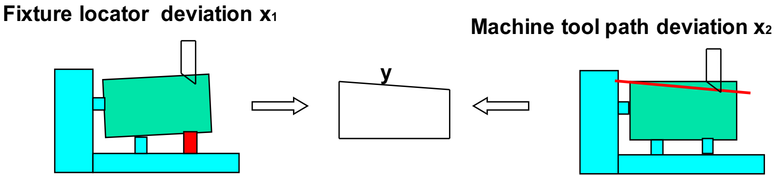
Question 1. How can we transfer the model to the new process condition/environment without repeating previous procedures?

Question 2. Could we figure out what was done in the recalibration?

Challenge of Model Transfer and Strategy Driven by Engineering Thinking

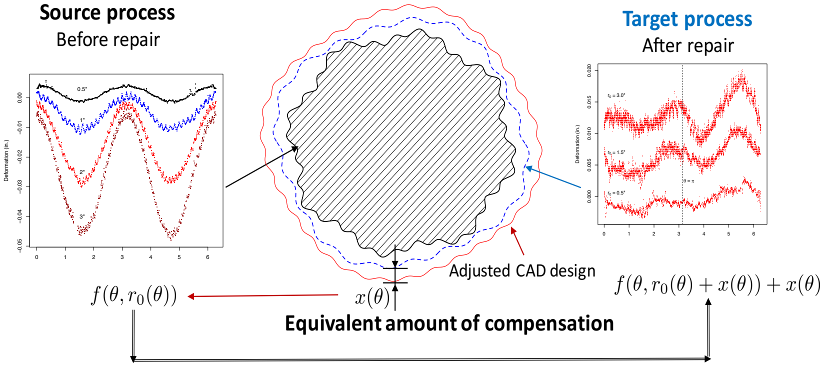
Main challenge: **Lurking variables** that are unknown or unobservable

Strategy: **Effect equivalence**, a common engineering phenomenon concerning the mechanism that different factors result in identical effects [Wang et al., 2005, Wang and Huang, 2006, Wang and Huang, 2007]



Effect Equivalence Approach to Handle Lurking Variables

Target process: "Nominal" shape (cylinder) printed after repair
Source process: "Actual" shape printed before repair
Bridge: "Compensated shape" to obtain the "nominal" shape

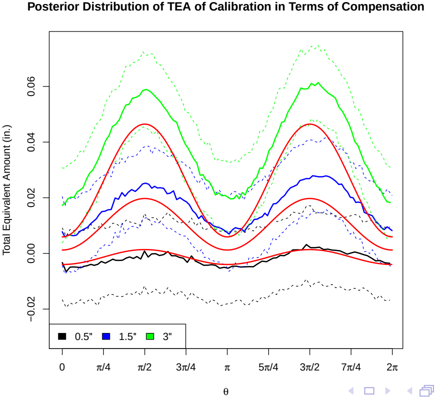


Model Transfer before and after Machine Calibration

– Estimate the total equivalent amount of lurking variable after calibration

[Sabbaghi and Huang, 2016]

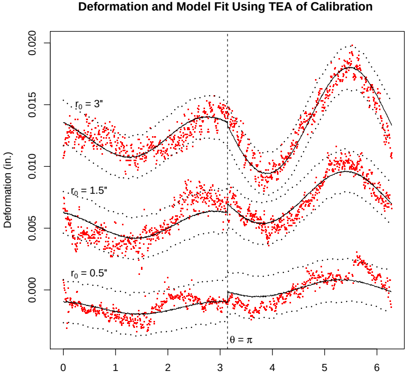
$$x(\cdot) = \mathscr{F}_S^{-1}(y_T) - \mathscr{F}_S^{-1}(y_S)$$



Model Transfer after Recalibration

Transfer the model before machine repair (A) to the process after repair (B)

$$\mathscr{F}_B(\cdot) = \mathscr{F}_A(\mathscr{F}_A^{-1}(y_A) + x(\cdot)) = f_A(\theta, r_0(\theta) + x(\theta)) + x(\theta)$$



[Sabbaghi and Huang, 2016]

Summary

For smart calibration of AM processes in a cybermanufacturing environment:

- Established prescriptive modeling approach to predict shape deformation based on limited trial shapes (forward problem)
- Established an analytical foundation to compensate 2D and 3D shape deformation (inverse problem)
- Developed Bayesian learning framework to learn from disparate data (learning problem)
- Establish a new model transfer scheme inspired by engineering thinking (transfer learning problem)

On-going and Future Work

- Prescriptive modeling of shape deformation of 3D freeform products
- Online monitoring and feedback control of AM processes
- Effect equivalence methods for transfer learning, modeling, and control
- Experimental design for AM processes
- Metrology: 3D scanning of 3D shape
- APP Development

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