Learning and Recalibration With Small Sets of Shapes for 3D Printing

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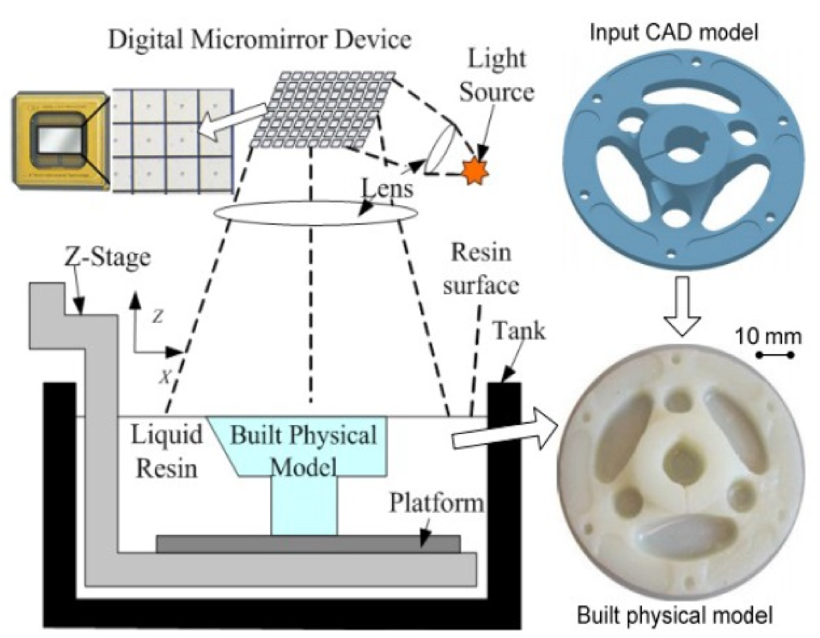
Paradigm Shift in Learning for Calibration



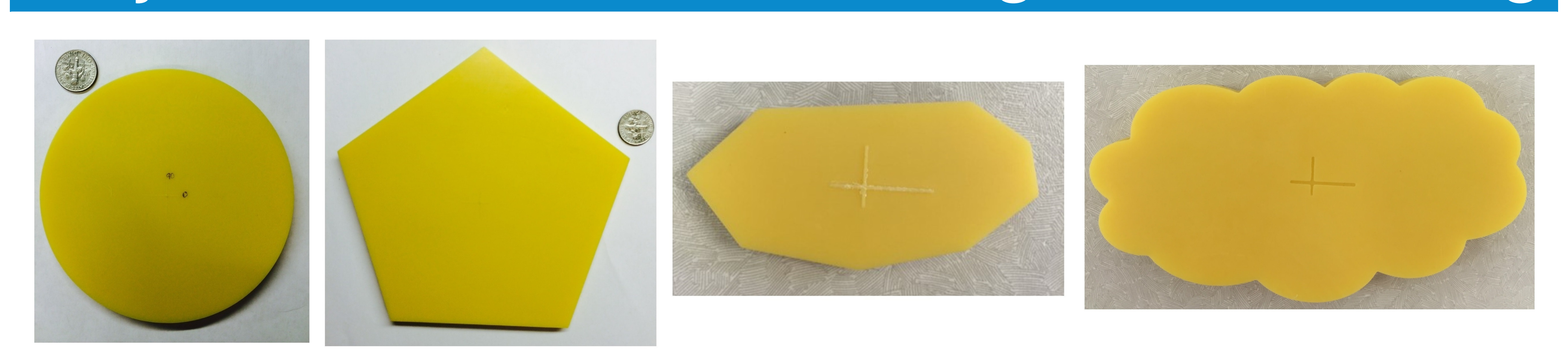
3D printing is a promising manufacturing technology marred by geometric shape deformation due to material solidification in the printing process.

Current "run-to-run" calibration methods use predictive deformation models to change the input CAD model and compensate for deformation.

Their common disadvantage is that experiments must be performed on several copies of each individual shape to learn deformation models.

The wide variety of process conditions and shapes, and the high operating cost of 3D printing, severely restrict the number of possible test cases.

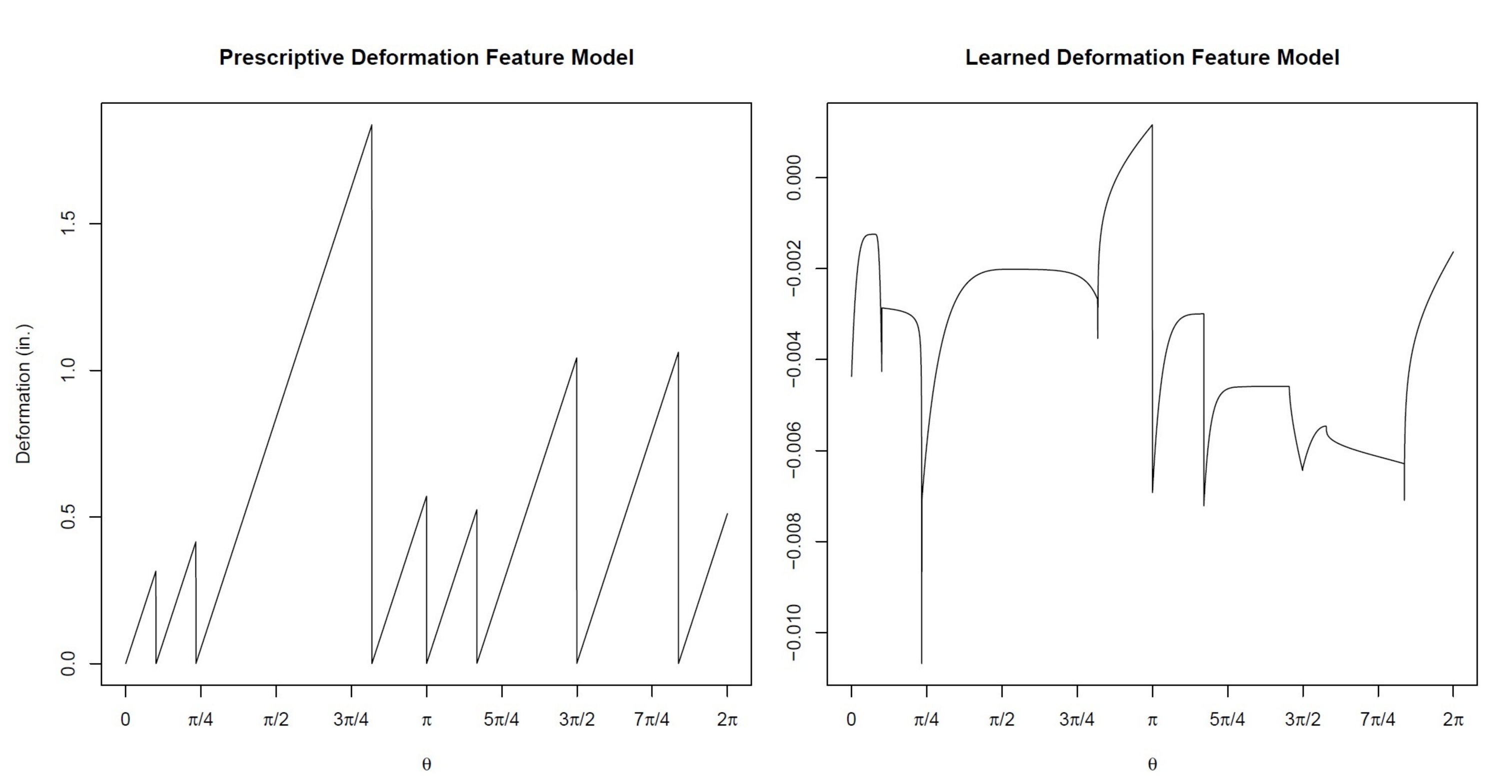
Objective: Efficient Learning in 3D Printing



Calibration of 3D printing requires efficient learning of deformation models for new shapes.

We developed a general Bayesian methodology for learning deformation models from just one new printed shape and a small sample of previously printed, different shapes.

Our methodology can also enable recalibration of ineffective deformation models and compensation plans with little further experimentation.



Background and Notation

We consider in-plane deformation for the individual layers of a 3D shape.

The Cartesian coordinates (x, y) of a printed shape are transformed to polar coordinates $(\theta, r(\theta))$ to decouple geometric shape complexity from learning of deformation models (Huang et al., 2015).

The input CAD model is represented by $r_0 : [0, 2\pi] \rightarrow \mathbb{R}$.

Deformation for a point θ on a printed shape $r_0(\cdot)$ is defined as

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

We connect deformation models of different shapes in a modular fashion using the "cookie-cutter" framework of Huang et al. (2014).

Deformation model for a previously manufactured, learned shape $r_0(\cdot)$:

$$\Delta r(\theta, r_0(\cdot)) = \delta_0(\theta, r_0(\cdot), \boldsymbol{\alpha}) + \epsilon_\theta.$$

Deformation model for a new, unlearned shape $r_1(\cdot)$:

$$\Delta r(\theta, r_1(\cdot)) = \delta_0(\theta, r_0(\cdot), \boldsymbol{\alpha}) + \delta_1(\theta, r_1(\cdot), \boldsymbol{\beta}) + \xi_\theta.$$

The δ_0 and δ_1 are deformation features, with δ_1 unique to $r_1(\cdot)$.

Bayesian Learning Methodology

1: Construct a discrepancy measure to extract information on δ_1 for a new shape $r_1(\cdot)$ based on a single newly printed shape and inferences on $\boldsymbol{\alpha}$ from previously printed shapes $r_0(\cdot)$.

$$T(\theta, r_1(\cdot)) = \Delta r(\theta, r_1(\cdot)) - \delta_0(\theta, r_0(\cdot), \tilde{\boldsymbol{\alpha}})$$

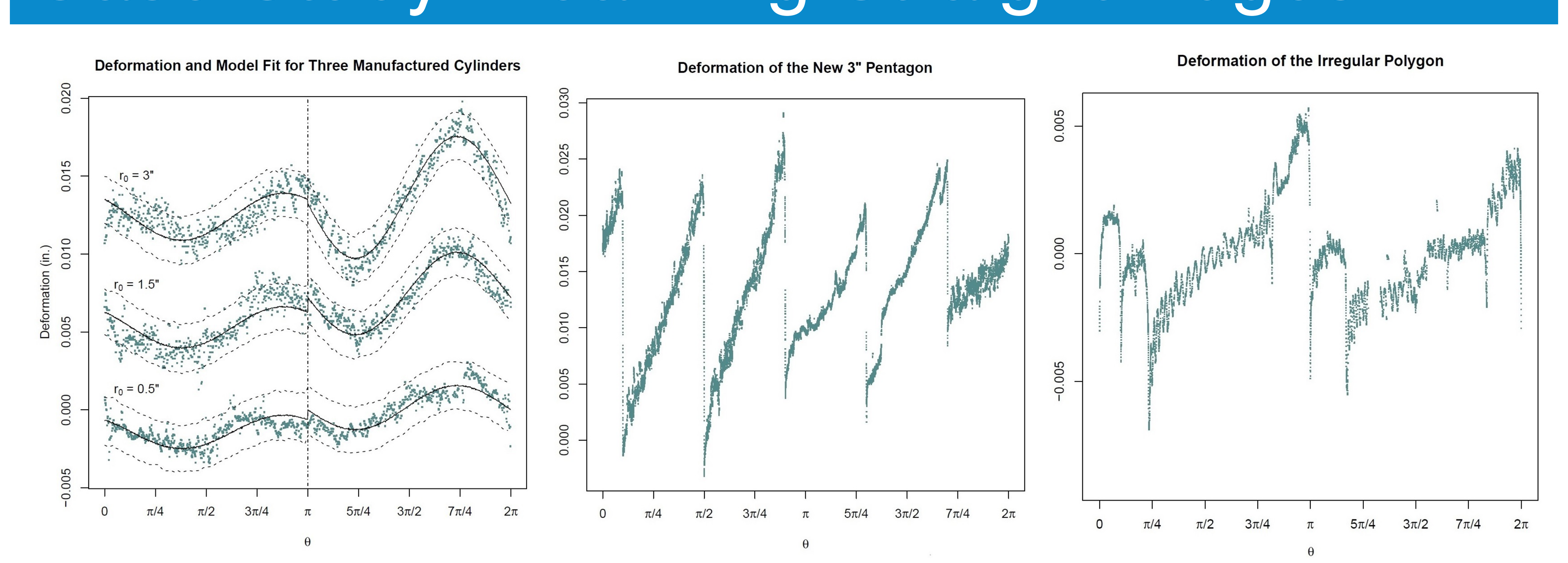
2: Stratify the discrepancy measures and test within and across strata to cluster points with distinct deformation feature trends.

$$\delta_1(\theta, r_1(\cdot), \boldsymbol{\beta}) = \sum_{k=1}^{K} \mathbb{I}(\theta \in \Theta_k)\delta_{1,k}(\theta, r_1(\cdot), \boldsymbol{\beta}_{e(\theta),k})$$

3: Specify a hierarchical model across strata for the $\boldsymbol{\beta}_{e,k}$ that can be extended to shapes possessing similar features as $r_1(\cdot)$.

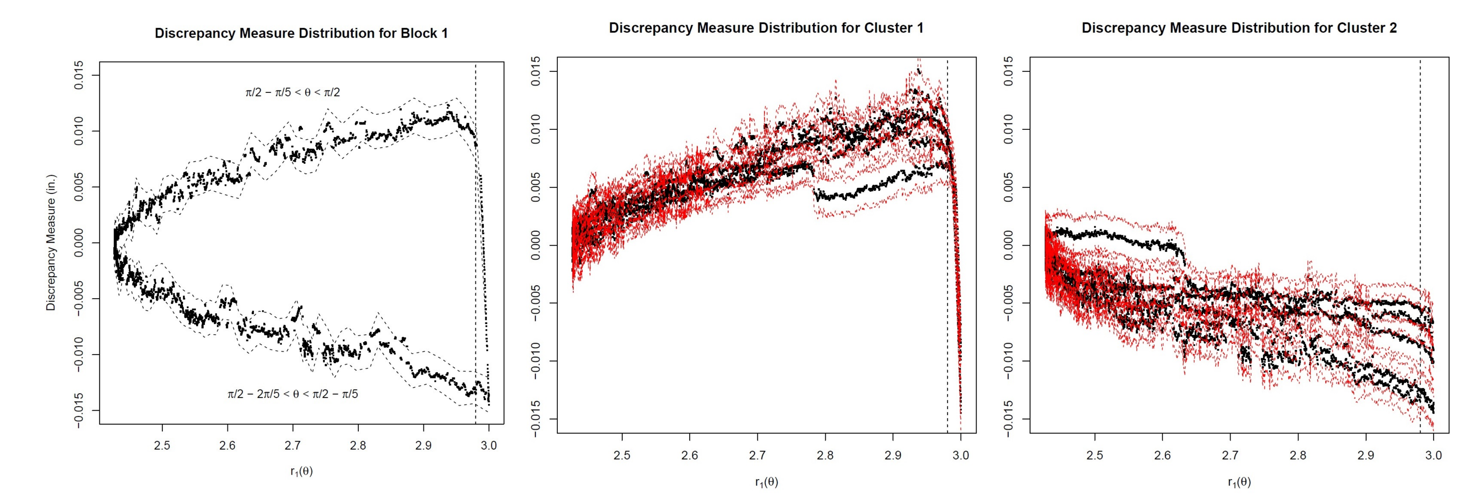
$$\boldsymbol{\beta}_{1,k}, \ldots, \boldsymbol{\beta}_{E,k} \mid \psi_k \sim p(\psi_k)$$

Case Study: Learning Straight Edges



Application of Bayesian Methodology

1 & 2: Extract and cluster discrepancy measures for one regular pentagon using inferences on α from three previously printed flat cylinders.

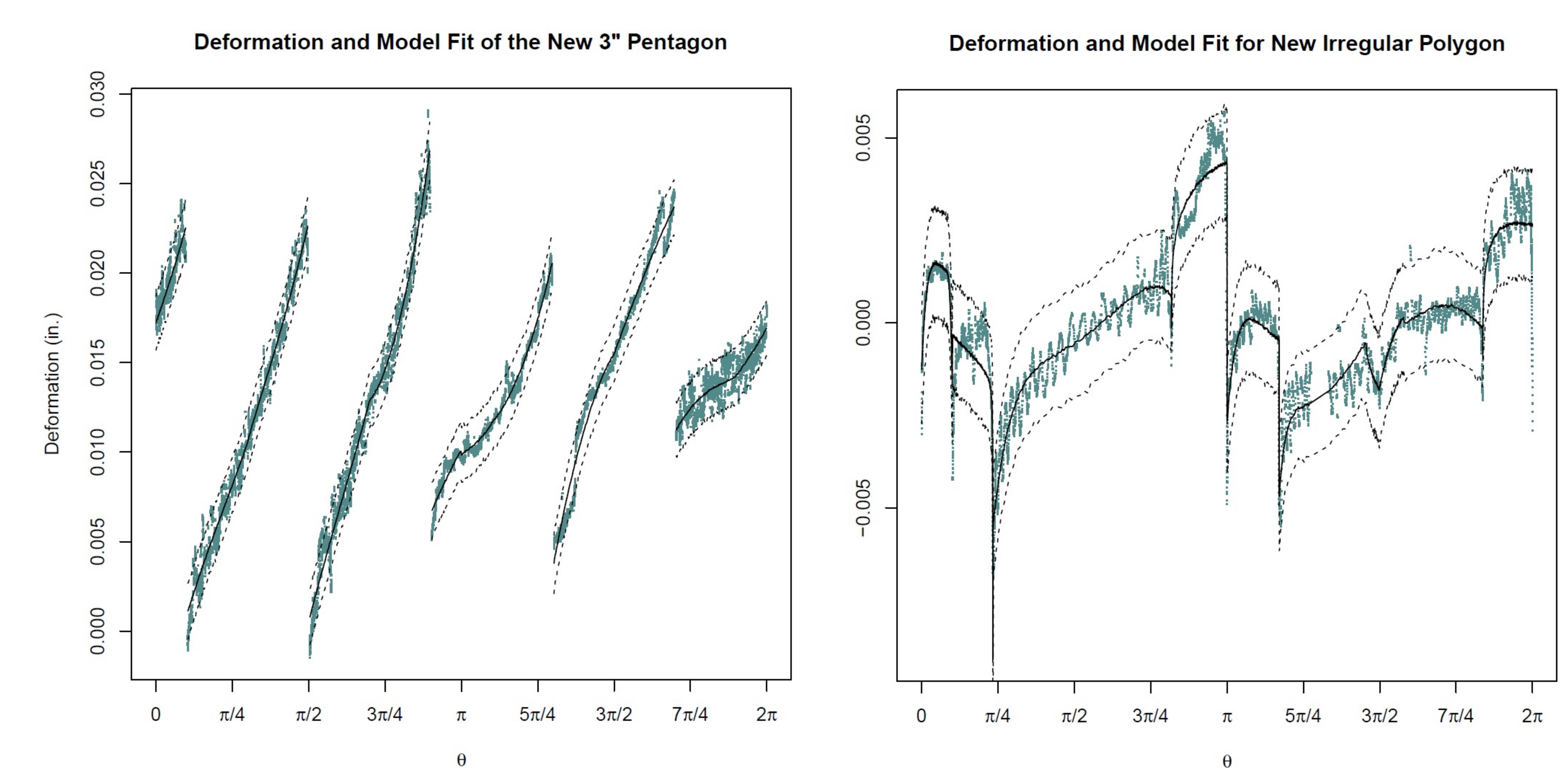


$$\delta_{1,k}\left(\theta, r_1(\cdot), \boldsymbol{\beta}_{e(\theta),k}\right) = \beta_{e(\theta),0} + \beta_{e(\theta),k,1}\left\{r_1(\theta) - r_1(m(\theta))\right\}^{b_{e(\theta),k}}$$

3: Specify hierarchical models for the $\beta_{e(\theta),0}$, $\beta_{e(\theta),k,1}$ across strata.

$$\beta_{e,k,1}, \ldots, \beta_{E,k,1} \mid \mu_k, \tau_k^2 \sim \mathrm{N}\left(\mu_k, \tau_k^2\right)$$

The learned deformation model is fit simultaneously to new shapes possessing straight edges, and old shapes.



Broader Impact and Future Work

After a new shape, compensated or uncompensated, has been printed, recalibration can be performed by using different discrepancy measures in the first step of our Bayesian methodology.

The broader impact of our procedure is smart 3D printing with the potential of immediate practical application.

Our next steps are to extend the methodology to free-form and 3D shapes, and incorporate the algorithms in our 3D printing deep learning app.

Acknowledgments

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