CMMI-1544917: CPS: Synergy: Collaborative Research: Smart Calibration Through Deep Learning for High-Confidence and Interoperable Cyber-Physical Additive Manufacturing Systems

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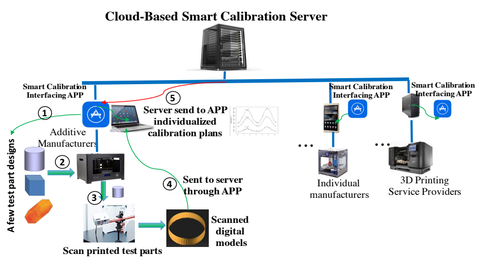
Project Objective

To establish smart and dynamic system calibration methods and algorithms through deep learning so as to enable high-confidence and interoperable cyber-physical additive manufacturing systems.



Background & Challenges

Background

- Quality control is indispensable link of the life-cycle of additive manufacturing (AM).
- One-of-a-kind AM fundamentally changes the paradigm of manufacturing operations.
- Cyber-Physical Additive Manufacturing Systems (CPAMS) is hyper-connected and globalized, which typically involve the aggregation of heterogeneous, and oftentimes distributed, manufacturing environments.
- There is a lack of cloud-based servers and APPs to provide AM communities fast calibration service.

Challenges

- In contrast to mass production, AM fabricates products with high shape complexity at extremely low volume.
- There are huge product varieties, but limited resources for machine calibration.
- Training data are disparate and limited, often generated under different process conditions.
- Traditional Statistical Quality Control is not directly applicable.
- These challenges introduce the need of new quality control methodologies for one-of-a-kind manufacturing.

Proposed Strategy

Smart calibration using limited data

Adjust product design to optimally compensation shape deviation

Fundamental research

1. **Forward problem:** to predict shape deviation by learning from limited number of test cases [Huang et al., 2015, Huang et al., 2014b, Sabbaghi et al., 2014, Luan and Huang, 2017a, Jin et al., 2016a]
2. **Inverse problem:** to find the optimal amount of compensation to minimize shape deviation [Huang et al., 2015, Huang, 2016]
3. **After-the-fact learning**: Learning for improved prediction of shape deviation given a newly printed product [Sabbaghi et al., 2015, Sabbaghi et al., 2017]
4. **Automated online learning**: fast and automatic model building for prescriptive prediction of shape deviation (Ferreira, Sabbaghi, Huang, 2017)
5. **Online statistical process control**: quick detection of process change from shape to shape and assessment of process capability (Luan, Post, Huang, 2017)

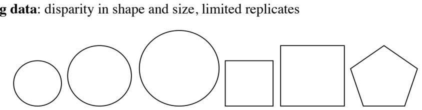
Statistical Process Control for CPAMS

Statistical Process Control (SPC) for AM Machines

Traditional SPC developed for mass production can hardly be applied to AM directly due to disparate shape data and sample size.

Problem description

Training data: disparity in shape and size, limited replicates



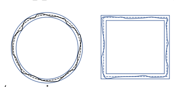
Assumption: training products fabricated under stable conditions

Objective: determining whether the process is in-control when building a new shape

A Prescriptive SPC Scheme for CPAMS

(i) Statistic: define a universal monitoring statistic applicable from shape to shape

$$\eta = \frac{|\Delta S|_{Actual}}{S_{Nominal}}$$



Intuition: percentage of area (2D) or volume (3D) shrinkage/expansion

(ii) Shape-shape-variation: adjust proactively the process variations from shape to shape to reduce false alarm rate

AM machines have variations changing from shape to shape, which may end up with large false alarm in process monitoring

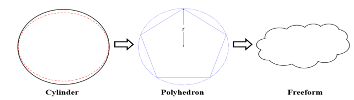
$$\eta_a = \frac{\left| |\Delta S|_{Actual} - \int_0^{2\pi} r_0(\theta) \left| f(\theta, r_0(\theta)) \right| d\theta \right|}{S_{Nominal}} \qquad \eta_b = \frac{\left| |\Delta S|_{Actual} - \int_0^{2\pi} r_0(\theta) \left| f(\theta, r_0(\theta) + x(\theta)) + x(\theta) \right| d\theta \right|}{S_{Nominal}}$$

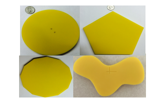
Intuition: remove the variation through predictive model

Prescriptive Prediction

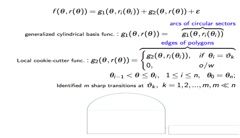
Prediction of Shape Deviation for Freeform Products

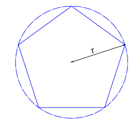
Select a limited number of test shapes to establish a prescriptive model enabling the prediction of freeform products [Huang et al., 2015, Huang et al., 2014b, Sabbaghi et al., 2014, Luan and Huang, 2017a]





Cookie-Cutter Modeling Framework [Huang, et al, 2014, Luan and Huang, 2017]





Control Charting and Capability Index

EWMA Control Chart (Luan and Huang, 2017b)

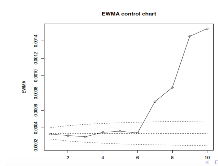


Table: Monitoring statistic η_i of validation data

Cross-section shape	$\lvert\Delta S\rvert_{Actual}$	$\lvert\Delta S\rvert_{Predicted}$	η $(\times 10^{-3})$
3″ dodecagon with compensation	0.07282	0	3.9575
1″ pentagon with compensation	0.01267	0	2.3245
$1''/\sqrt{2}$ square inner	0.02729	0.00351	6.7521
$2''/\sqrt{2}$ square before repair	0.05461	0.03812	2.3446

EWMA control chart

Process Capability Index C_p for AM Processes

A process capability index invariant to shape changes

$$C_p = \frac{USL - \mu_\eta}{3\sigma_\eta}$$

Estimation of μ_η and σ_η

$$\hat{\mu}_\eta = \bar{\eta}; \quad \hat{\sigma}_\eta = \frac{\overline{MR}}{d_2}$$

where $MR_i = |\eta_i - \eta_{i-1}|$, and d_2=1.128.

Conclusion

- Establish a SPC scheme to prescriptively monitor CPAMS
- Introduce a process capability measure for AM
- Validate the SPC scheme in a real AM (SLA) process .