# Predict Shape Distortion of 3D Printed Products Through Engineering-Informed Machine Learning

Dr. Qiang Huang (Lead PI) <u>Video Link</u>: https://youtu.be/cYu7Nmo2iiA University of Southern California (USC) <u>Group Link</u>: HuangLab.usc.edu <u>Ema</u>il: qiang.huang@usc.edu

- To enable high-confidence and interoperable cyber-physical additive manufacturing systems (CPAMS), it is critical to establish smart and dynamic system calibration methods under a highly heterogenous learning environment.
- Engineering-informed machine learning approaches are more suitable to predict and control the shape distortion of 3D printed products, and to provide process insights.

### **Challenges in Shape and Process Complexities**

- Shapes of AM built products: infinite variety [Kendall et al., 2009, Sharon and Mumford, 2006, Dryden and Mardia, 2016]
- Sample size for each shape: one-of-a-kind Mfg  $(N \approx 1)$  vs. mass production  $(N \approx \infty)$ : AM often faces limited training samples for individual shapes.
- Process complexity: Varying materials, process conditions, and machines The same shape of different sizes can have different deformation patterns due to the layer-by-layer fabrication process. [Jin et al., 2019, Huang et al., 2019]





#### **Strategy and Solution**

- Establish an engineering-informed Convolution Learning for AM
- Understand the layer interaction and deformation accumulation
- Integrate 2D and 3D shape deformation learning

### Smart Calibrators for CPAMS

Enable a cloud-based calibration and shape distortion control service for 3D printing users and manufacturers



### **Education and Outreach**

- Promote interdisciplinary training and education
- Promote international collaboration among faculty and PhD students
  FACAM workshop at ENS Paris-Saclay, 2019 (https://facam-online.blogspot.com/)



## **Broader Impact**

 Improve 3D printing shape accuracy by 50% or more through machine learning with small training samples

Convolution formulation

 $(f * g)(\mathbf{x})$ 

• Extend to medical and aerospace industries



## **Scientific Impacts on CPS**

- Establish an engineering-informed ML method to learn heterogeneous data in CPAMS
- Provide a path for model and knowledge transfer from shape to shape and process to process.
- Obtain engineering insights



$$\begin{split} y\big(r_0(\theta,\varphi),\theta,\varphi,\big) &= (f*g)\big(r_0(\theta,\varphi),\theta,\varphi\big) + \mathcal{GP}(0,k(\cdot,\cdot)) + \epsilon' \\ &- \text{Layer-by-layer fabrication process and math integration:} \end{split}$$



Transfer function

 $g(k), g(k-1), \dots, g(1)$ 

- System inputs, transfer function, and convolution formulation:

RI

2019 NSF Cyber-Physical Systems Principal Investigators' Meeting November 21-22, 2019 | Crystal City, Virginia