Image-guided Additive Manufacturing

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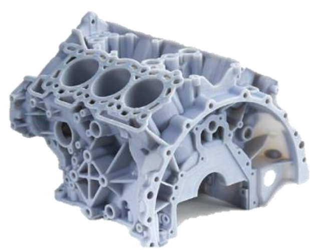
Outline

- Research Motivation
- Research Methodology
  - Network Representation of Image Profiles
  - Network Community Modeling and Characterization
  - Multivariate Monitoring of Network Statistics
- Preliminary Study
- Conclusions

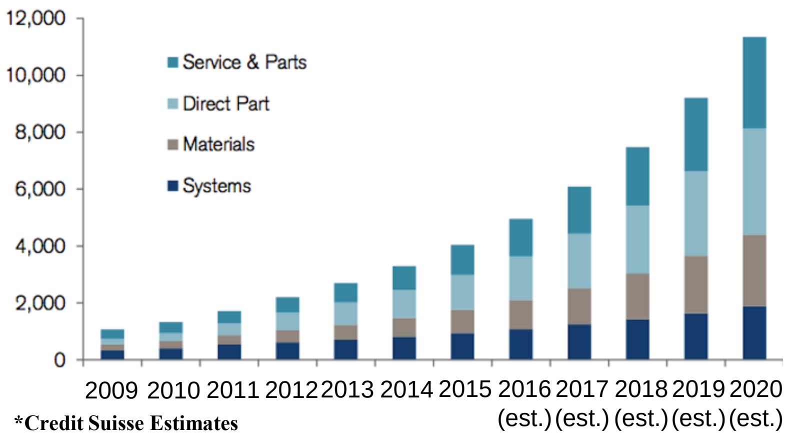
Introduction

- **Highly customized, high flexibility**



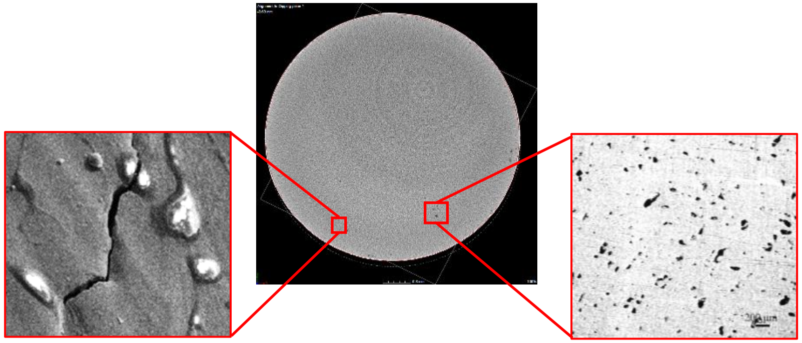
- **Long post-build inspection and finish**

- **Rapid growth of market**



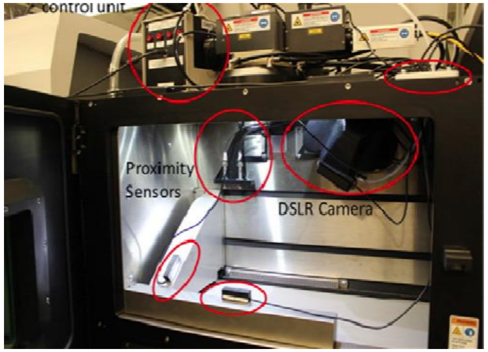
*Credit Suisse Estimates

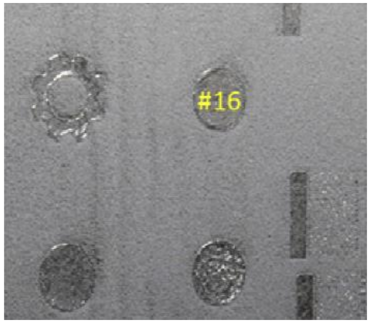
- **High rejection rate (>2%)**



Micro cracks *Porosity*

In-situ Imaging Data





Selective laser sintering/melting with DSLR cameras

CT scanner

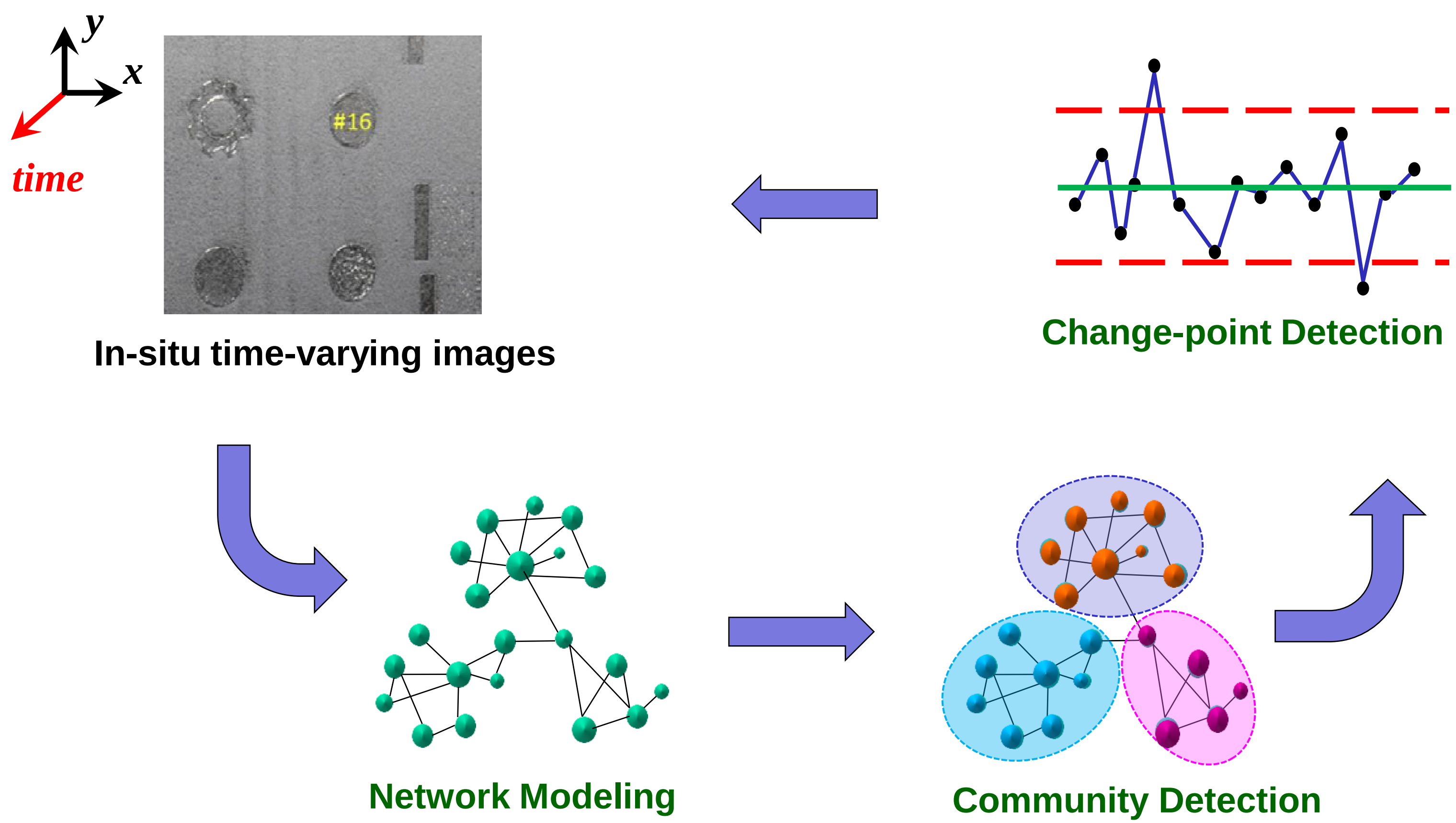
State of the Art

- **1-D Profile Monitoring:** Linear regression model (Kang and Albin 2000), Wavelet decomposition (Zhou, Sun and Shi 2006, Paynabar and Jin 2011)
  - Not applicable for 2-D image profiles
- **2-D Image Monitoring:** Image processing + B-spline (Park et al. 2014), Gaussian process (Zhang, Wang and Chen 2015), Low-rank tensor decomposition(Yan, Paynabar and Shi 2015)
  - Focus on snap-shot images of discrete samples
- **Time-varying 2D and 3D images?**

→ **Need to fill in the gap**

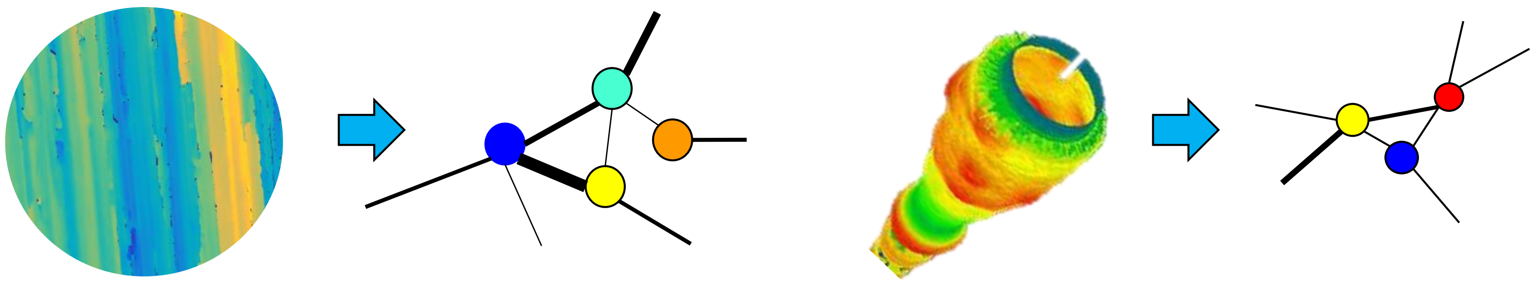
Research Objective

Develop a dynamic network scheme to represent, model and control time-varying image profiles

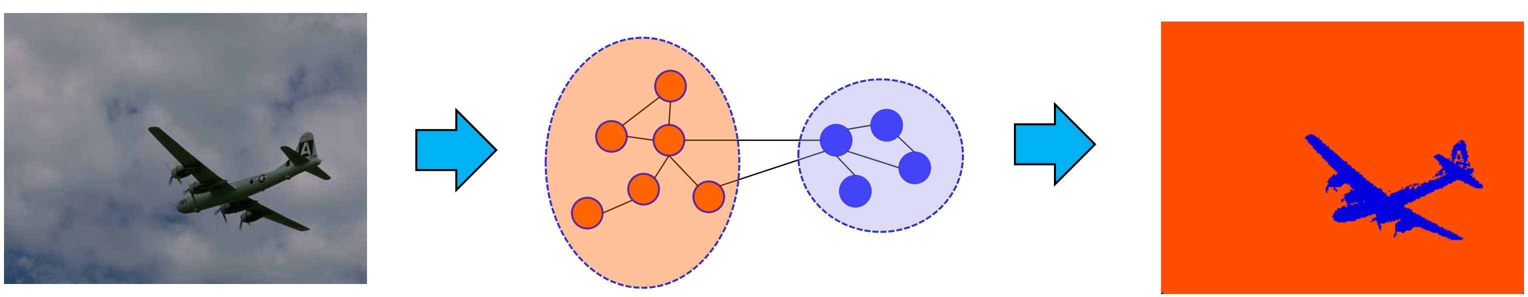


Advantages of Dynamic Network

- High-dimensional data representation



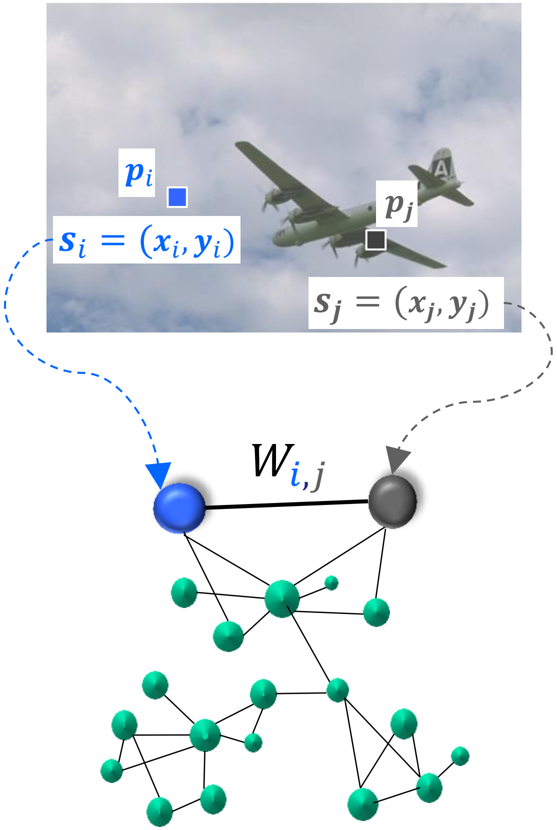
- Network communities ↔ Image patterns



Network Representation

- Weighted network ⇨ Intensity difference + Spatial closeness

$$W_{i,j} = \exp\left(\frac{\alpha \left|\boldsymbol{p}_i - \boldsymbol{p}_j\right|^2 + (1-\alpha)\left|\boldsymbol{s}_i - \boldsymbol{s}_j\right|^2}{2 \times l^2}\right)$$



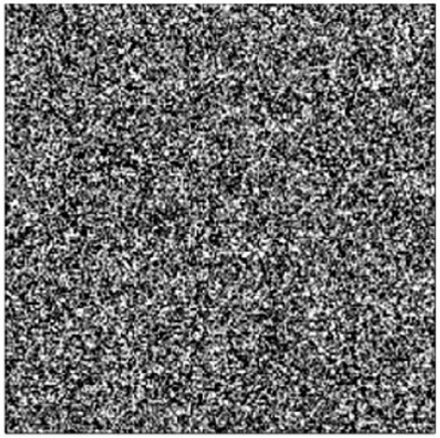
$\boldsymbol{p}_i$ – *Intensity value of pixel* i

$\boldsymbol{s}_i$ – *Spatial location of pixel* i

l – *Kernel bandwidth*

$\alpha \in [0,1]$ – *Regularization parameter*

Network Representation

A

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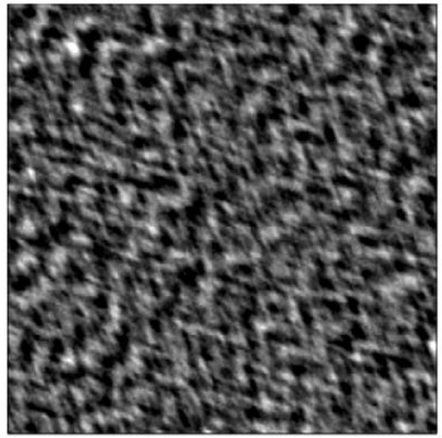
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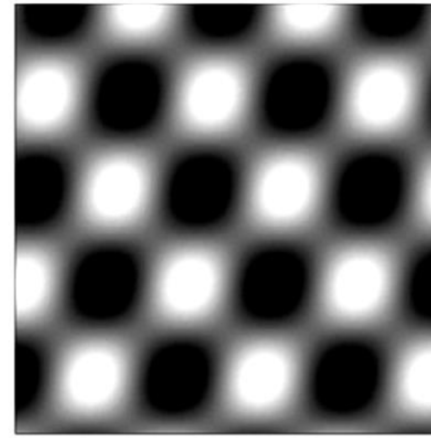
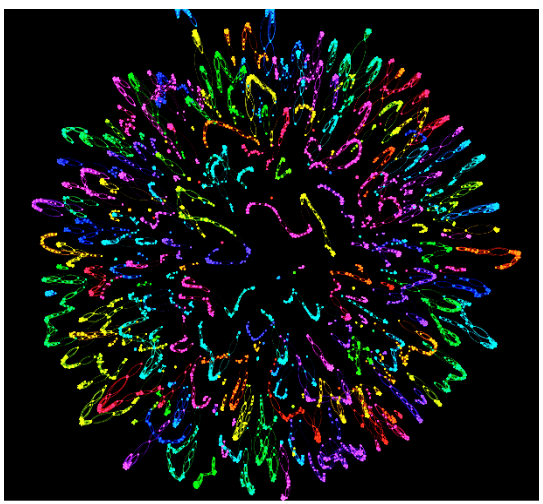
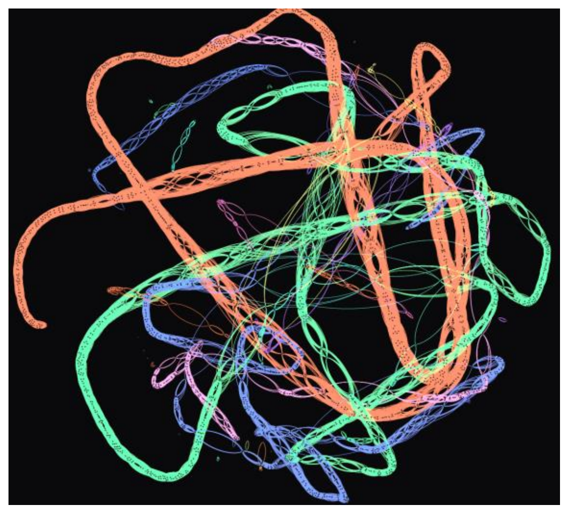
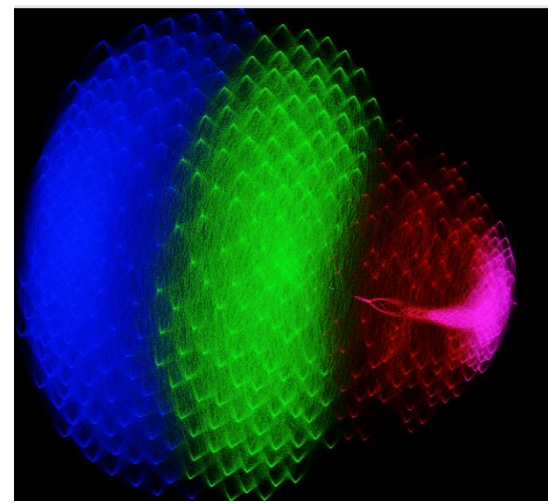


Random Noise | *Auto regression* | *Periodic*

Community Detection

- Potts model Hamiltonian

$$\min_{(g_i, g_j)} \left\{ \mathcal{H}\left(\{g_i, g_j\}_{i=1}^{N} \right) \right\}$$

$$\mathcal{H}(g_i, g_j) = \frac{1}{2} \sum_{k=1}^{K} \sum_{i,j \in C_k} (W_{ij} - \bar{W})[\Theta(\bar{W} - W_{ij}) + \gamma \Theta(W_{ij} - \bar{W})]\delta(g_i, g_j)$$

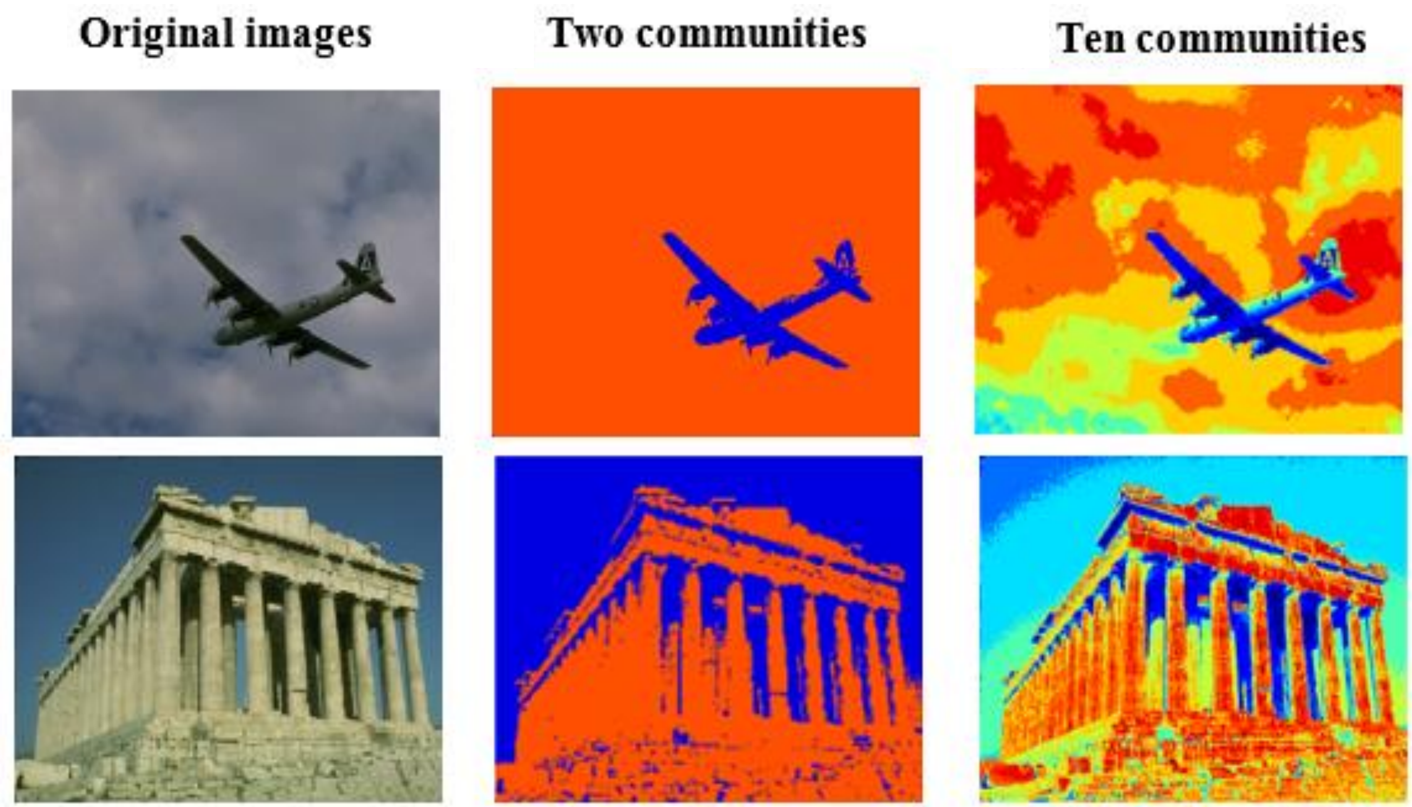
Hamiltonian within a community

Hamiltonian of a whole network

s.t. $1 \le g_i, g_j \le K, \quad 1 \le i, j \le N$

- g_i – *"Potts type" variable → community label of node* i, $g_i \in [1, K]$
- $\bar{W}$ – *the average of all weights*
- γ – *the regularization parameter*
- $\Theta(\cdot)$ – *the Heaviside function*
- $\delta(g_i, g_j)$ – *the Kronecker delta*

Community Detection on Sample Images



Main objects

Detailed patterns

Network Generalized Likelihood Ratio Chart

- Normality assumptions
  - *Pixel intensity within the community* $C_k \sim N\left(\mu_k^{(i)}, {\sigma_k^{(i)}}^2\right)$
  - *Community statistics from sample to sample are normally distributed.*

- A vector of community statistics

$$\boldsymbol{y}^{(i)} = \left(\bar{x}_1^{(i)}, \dots, \bar{x}_K^{(i)}, s_1^{(i)}, \dots, s_K^{(i)}, n_1^{(i)}, \dots, n_K^{(i)}\right)^T$$

Before shift: $\boldsymbol{y}^{(i)} \sim MVN(\boldsymbol{\mu}_0, \boldsymbol{\Sigma})$ *After shift:* $\boldsymbol{y}^{(i)} \sim MVN(\boldsymbol{\mu}_1, \boldsymbol{\Sigma})$

- Hypothesis testing

$$\begin{cases} H_0:\ E[\boldsymbol{y}^{(i)}]_{i=1}^{\tau} = E[\boldsymbol{y}^{(i)}]_{i=\tau+1}^{m} = \boldsymbol{\mu}_0 \\ H_1:\ E[\boldsymbol{y}^{(i)}]_{i=1}^{\tau} \neq E[\boldsymbol{y}^{(i)}]_{i=\tau+1}^{m} = \boldsymbol{\mu}_1 \end{cases}$$

Network Generalized Likelihood Ratio Chart

Likelihood function

Under H_0

$$L(\boldsymbol{\mu}_0) = \prod_{i=1}^{m} \frac{1}{(2\pi)^{\frac{Q}{2}}|\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}\left(\boldsymbol{y}^{(i)} - \boldsymbol{\mu}_0\right)^T \boldsymbol{\Sigma}^{-1}\left(\boldsymbol{y}^{(i)} - \boldsymbol{\mu}_0\right)\right)$$

Under H_1

$$L(\boldsymbol{\mu}_0, \boldsymbol{\mu}_1) = \left(\frac{1}{(2\pi)^{\frac{Q}{2}}|\boldsymbol{\Sigma}|^{\frac{1}{2}}}\right)^m \times \prod_{i=1}^{\tau} \exp\left(-\frac{1}{2}\left(\boldsymbol{y}^{(i)} - \boldsymbol{\mu}_0\right)^T \boldsymbol{\Sigma}^{-1}\left(\boldsymbol{y}^{(i)} - \boldsymbol{\mu}_0\right)\right) \times \prod_{i=\tau+1}^{m} \exp\left(-\frac{1}{2}\left(\boldsymbol{y}^{(i)} - \boldsymbol{\mu}_1\right)^T \boldsymbol{\Sigma}^{-1}\left(\boldsymbol{y}^{(i)} - \boldsymbol{\mu}_1\right)\right)$$

Online GLR statistics

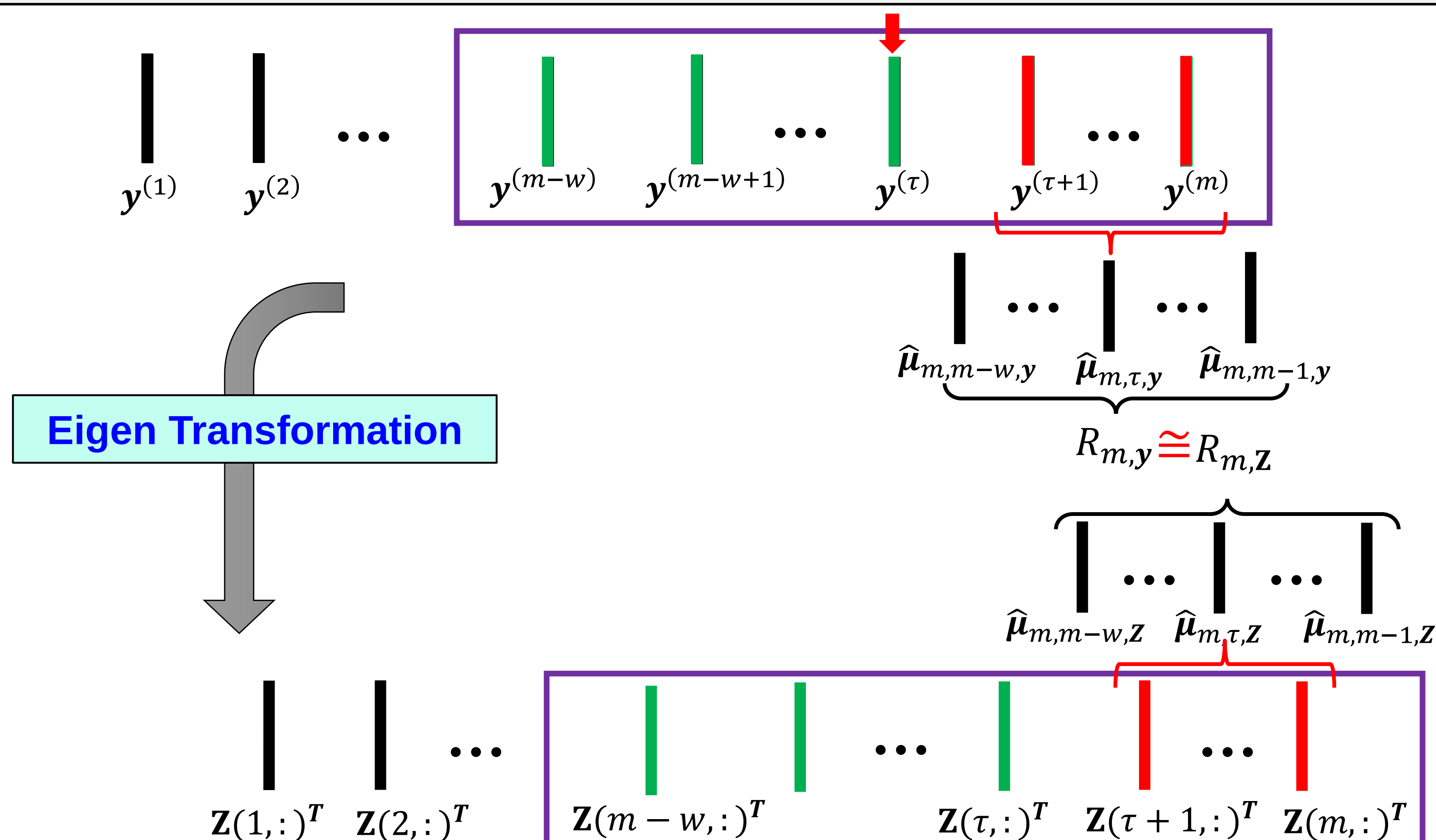
Singular?

$$R_{m,y} = \max_{\max(0,m-w)\le\tau<m} \frac{m-\tau}{2} \left(\widehat{\boldsymbol{\mu}}_{m,\tau,y} - \overline{\boldsymbol{y}}\right)^T \boldsymbol{S}^{-1} \left(\widehat{\boldsymbol{\mu}}_{m,\tau,y} - \overline{\boldsymbol{y}}\right)$$

NGLR in the Eigenspace

Proposition: In the eigenspace, multivariate GLR statistic is represented as:

$$R_{m,\mathbf{Z}} = \max_{\max(0,m-w)\le\tau<m} \frac{m-\tau}{2}\left(\hat{\boldsymbol{\mu}}_{m,\tau,\mathbf{Z}}\right)^T \boldsymbol{S}_{\mathbf{z}}^{-1}\left(\hat{\boldsymbol{\mu}}_{m,\tau,\mathbf{Z}}\right), \quad \hat{\boldsymbol{\mu}}_{m,\tau,\mathbf{Z}} = \frac{1}{(m-\tau)}\sum_{i=\tau+1}^{m} \mathbf{Z}(i,:)^T$$



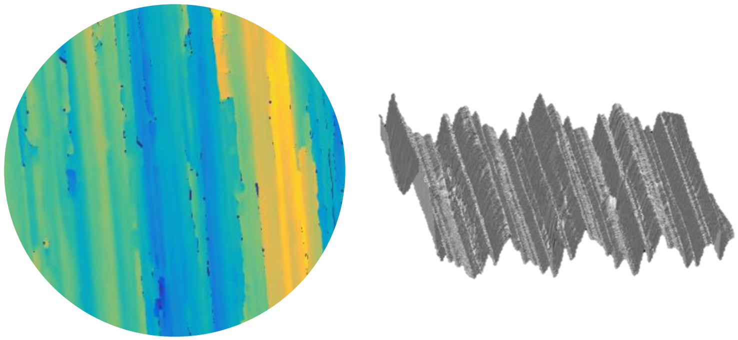
Preliminary Study – Ultraprecision Machining

(*mm*)

(*μm*)

(*nm*)

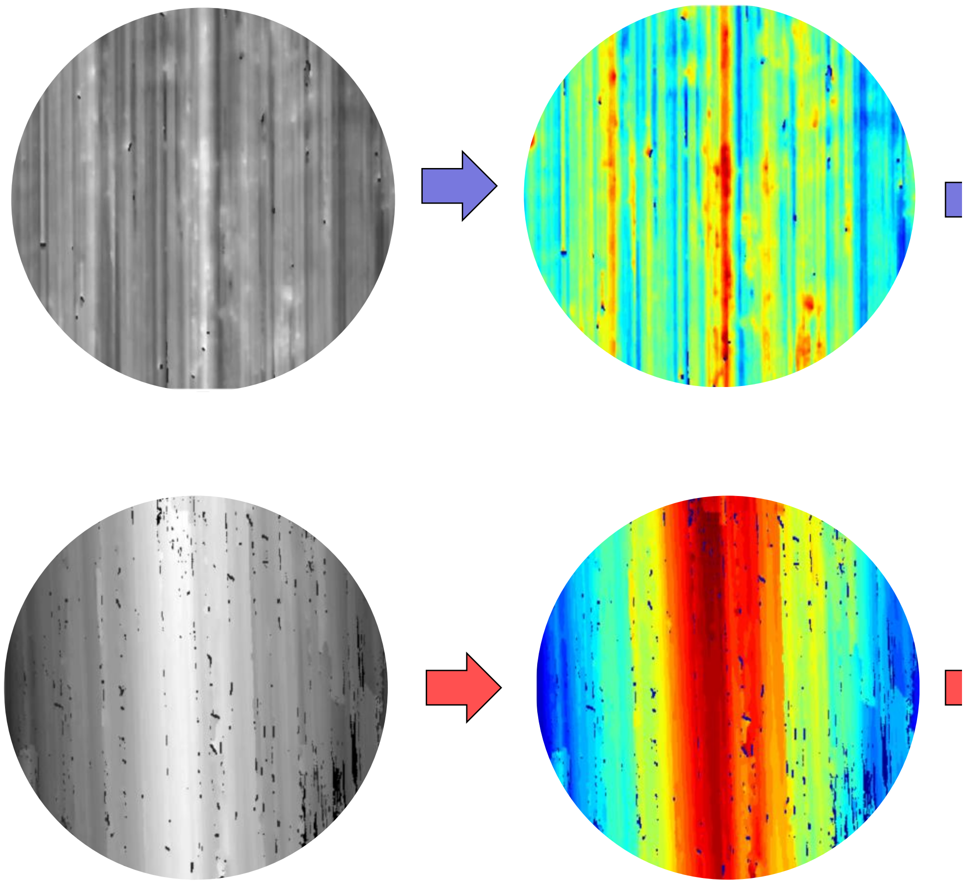
Microxam interferometric surface microscope

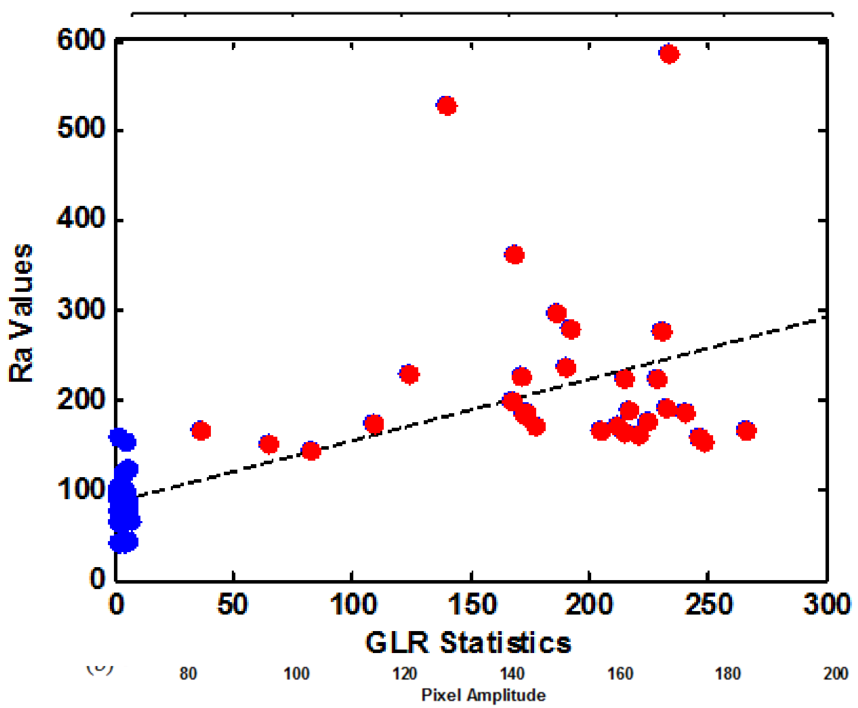


UPM surface images

Preliminary Study – Ultraprecision Machining

Original image | *Community detection result* | *Distribution of community statistics*

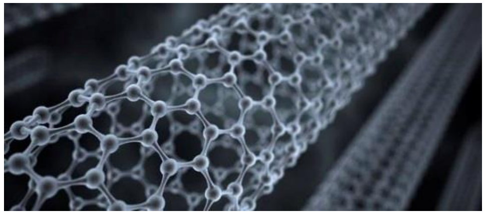




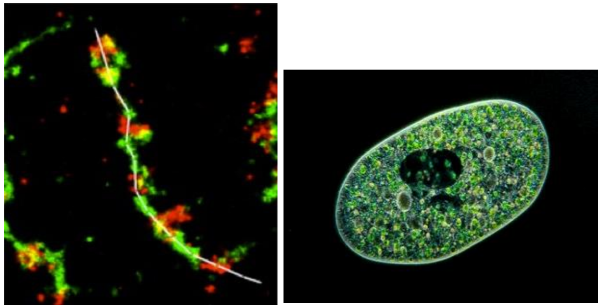
Conclusions

Our proposed approach		Existing practices
In-process control	*vs.*	Post-build inspection
High-dimensional images	*vs.*	Low-dimensional quality variables
Dynamic image streams	*vs.*	Static images

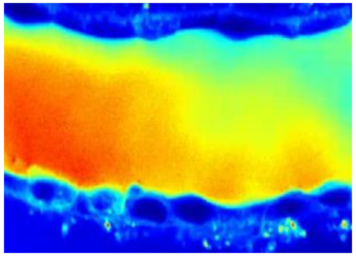
Applications



Nano-manufacturing



Medical research



Bio-manufacturing


Thank you!