Georgia Tech ISyE
H. Milton Stewart School of Industrial and Systems Engineering

# Machine Learning Enabled Quality Improvement in Smart Manufacturing

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# Outline

- Introduction
- Two Examples for ML Enabled Quality Improvement
  - Sparse Learning and Control in Fuselage Assembly
  - Dynamic Multivariate Functional data Modeling via Sparse Subspace Learning
- Summary

# What is Smart Manufacturing?

**Smart manufacturing is a combination of the major innovations in information and digital technology:**

- Sensors
- Internet of Things
- Big Data
- Cloud Computing
- AI and Machine Learning
- Advanced Mfg System
- Cyber Security
- Robotics and Automation
- Algorithms & Virtualization
- Data Fusion Analytics

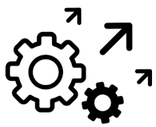
**Smart Manufacturing**

**The broad coalition of new technologies enables new manufacturing capabilities to achieve high quality, productivity, flexibility with reduced cost.**

# Key Component: System Data Analytics

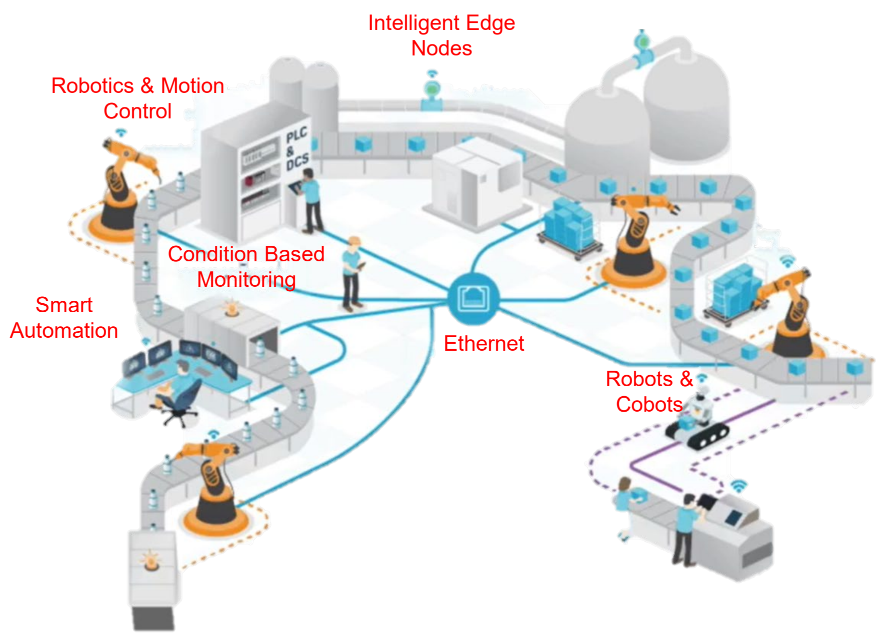
## Integrate Engineering Domain Knowledge and Advanced Data Analytics to Enable Smart Manufacturing

**Product Improvement**



**Process Improvement**

**Real-time Demand Forecasting**




**Cyber Security**

**Predictive Maintenance and Control**

**Monitoring, Diagnosis, Prognostics**

**Interconnected System**

**Data Fusion and ML**

**This talk focuses on <u>Machine Learning Enabled Quality Improvement</u>**

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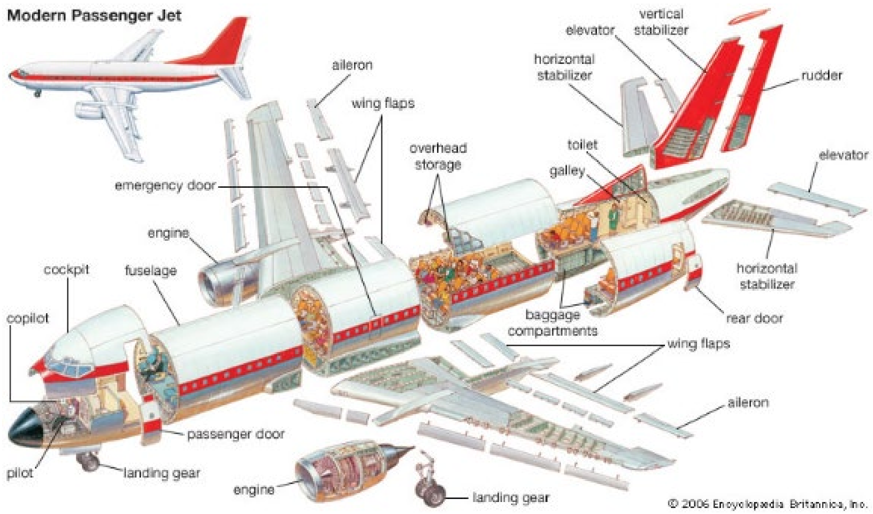
# Fuselage Assembly and Dimension Variation
# - Shape Control of Fuselage



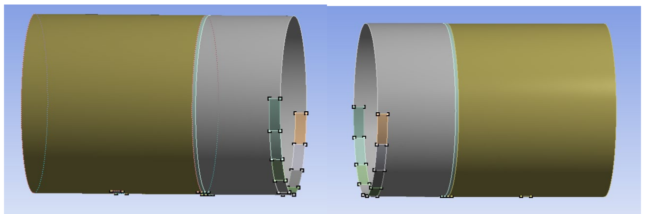

## Current Practice

- Manual shimming to reduce the dimensional deviations and get the required shape of the parts.
- The adjustment is conducted by using **trial and error** method.

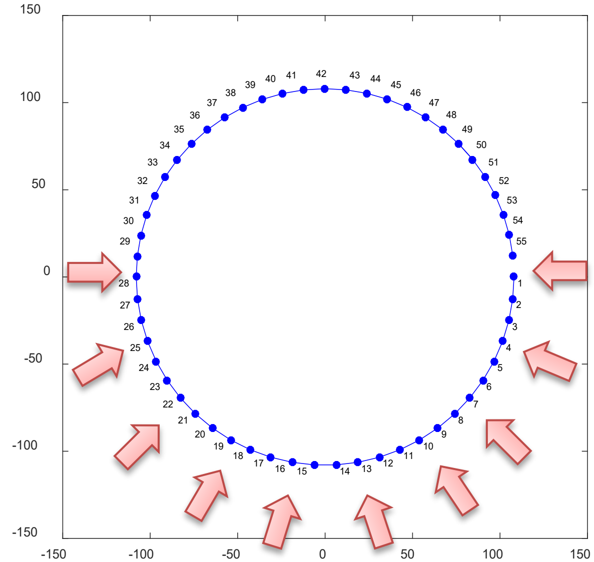
## Limitations of the Current Practice

- **low efficiency:** it may take longer time and multiple trials to adjust actuators to achieve the desired shape/dimension;
- **Non-optimal**: it may reach an acceptable dimensional quality rather than the optimal deviation reduction.
- **Highly skilled engineers required**: the effectiveness and efficiency of assembly depends on the skills of engineers.

# GOAL: Automatic Optimal Shape Control (AOSC) System

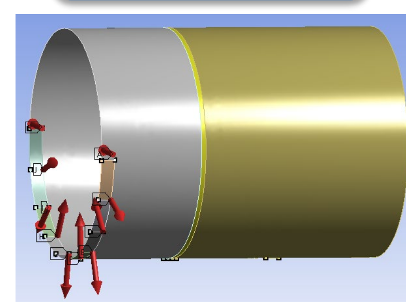


**Section 41** **Section 43**




*Start here* → **Sections Line Up** → **3D Laser Metrology** → **Automatic Optimal Shape Control System** → **Deformation Control** → **Measurement Confirmation & Assembly** → *End here*

- **SoV Model Prediction;**
- **Iterative Virtual Shape Adjustment;**
- **Optimal forces applied via actuators**



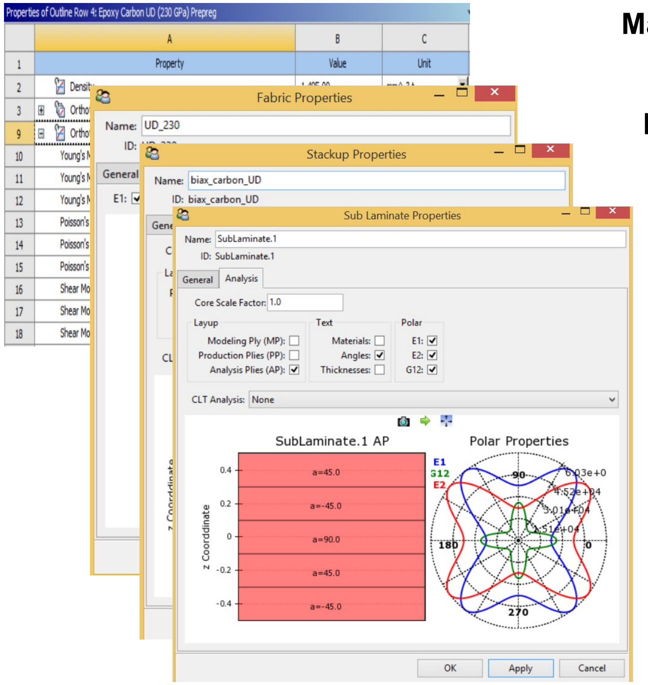
***Advantage:***

***Reduce flow time; Increase productivity; Achieve high quality; Applicable to all part joins.***

# Sparse Learning and Model Calibration for Composite Fuselage Shape Control

- Wang, Y., Yue, X., Tuo, R., Hunt, J. H., Shi, J., 2020 "Effective Model Calibration via Sensible Variable Identification and Adjustment, with application to Composite Fuselage Simulation", *The Annals of Applied Statistics,* Vol. 14, No. 4, 1759–1776 https://doi.org/10.1214/20-AOAS1353 (This paper won the QSR Best Refereed Paper Finalist Award for the 2017 INFORMS Conference.)
- Du, J., Yue, X., Hunt, J. H., and Shi, J. 2019." Optimal Placement of Actuators via Sparse Learning for Composite Fuselage Shape Control." *Journal of Manufacturing Science and Engineering*, Vol.141, No.10.pp1-37.

# FEA Simulation Platform and Validation

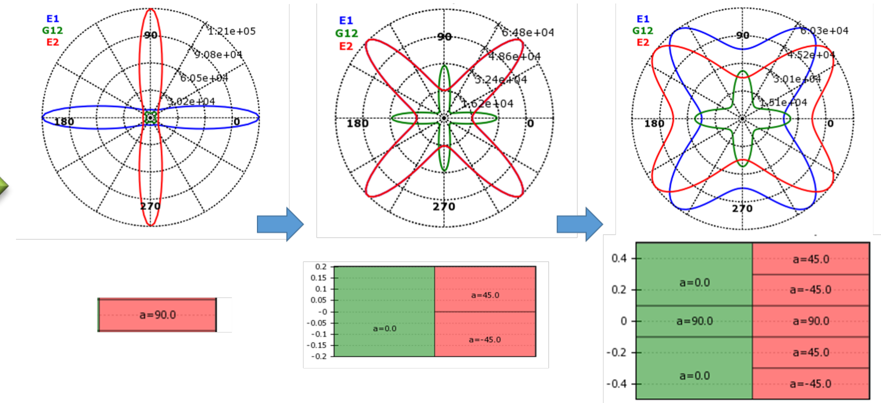



Material: Carbon Fiber & Resin Epoxy

Fabrics

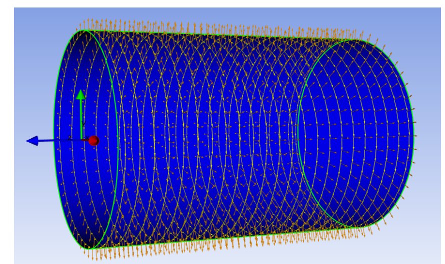
Stackups

Sub Laminates

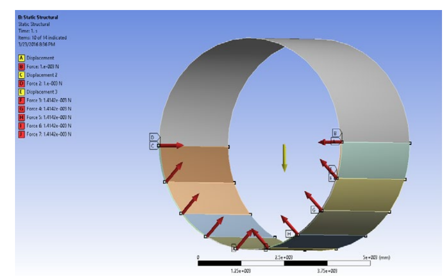



(a) (b) (c)

Fabrication Process

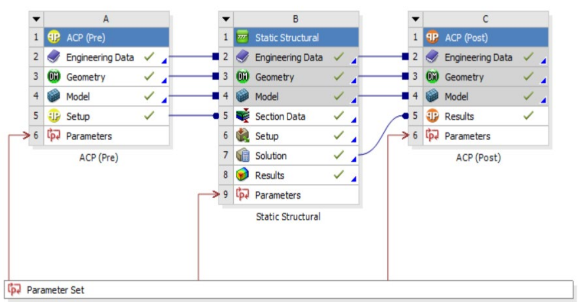


Carbon Fiber Orientation



Ten Actuators

ANSYS Workbench: Composite Prepost




***Note:* The FEA model mimics the real fabrication process of the large composite fuselage.**


Wen, Y., Yue, X., Hunt, J. H., Shi, J., 2018, “Feasibility Analysis of Composite Fuselage Shape Control via Finite Element Analysis”, Journal of Manufacturing Systems, Volume 46, Pages 272-281

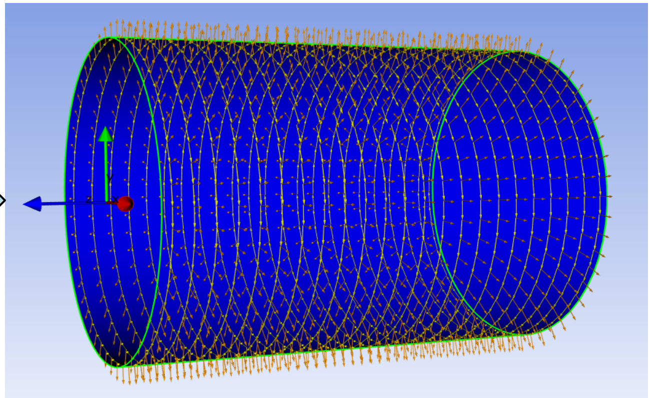
# Model Calibration via Sensible Variable Identification

- **Goal**: find the optimal values of the model parameters, under which the finite element outputs match the structural load experimental observations of the composite fuselage;
- **Challenge:**
  **Limited Physical Experiment Sample**: the corresponding physical experiment is expensive to run
  **Many Model Parameters**: computer experiments may have a number of calibration parameters.

$$\hat{\theta}_n = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, L(\boldsymbol{Y}^p, \boldsymbol{Y}^s_{\boldsymbol{\theta}}) + \lambda_n \parallel \boldsymbol{\theta} - \boldsymbol{\theta}_0 \parallel$$

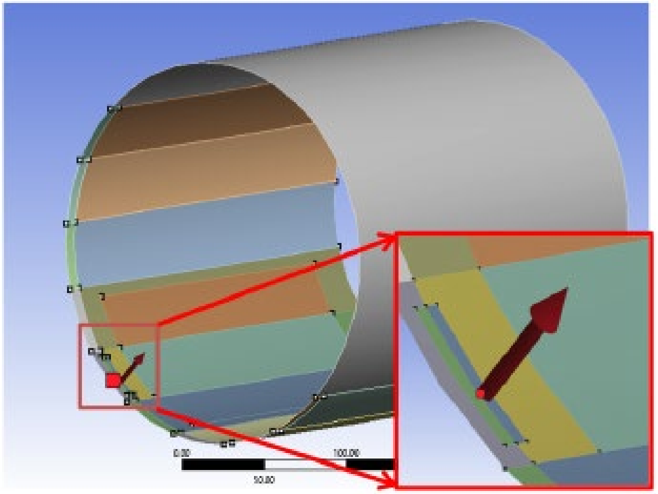
$$= \underset{\boldsymbol{\theta}}{\operatorname{argmin}} (\boldsymbol{Y}^p - \boldsymbol{Y}^s_{\boldsymbol{\theta}})^T (\tau^2 \boldsymbol{\Phi}_\theta + \sigma^2 I_n)^{-1} (\boldsymbol{Y}^p - \boldsymbol{Y}^s_{\boldsymbol{\theta}}) + \lambda_n \sum_{i=1}^{m} |\theta_i - \theta_i^{(0)}|$$

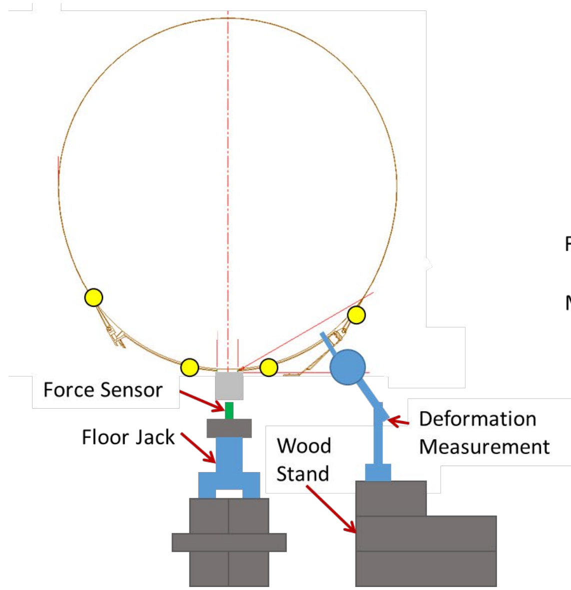
Sensible Variable Properties:
- Sensitivity
- Suboptimality
- Sparsity

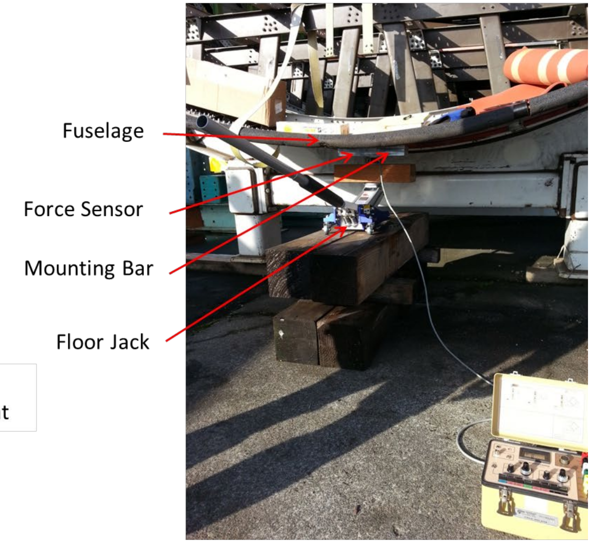


Wang, Y., Yue, X., Tuo, R., Hunt, J. H., Shi, J., 2020 "Effective Model Calibration via Sensible Variable Identification and Adjustment, with application to Composite Fuselage Simulation", *The Annals of Applied Statistics,* Vol. 14, No. 4, 1759–1776 (This paper won the QSR Best Refereed Paper Finalist Award for the 2017 INFORMS QSR Section.)

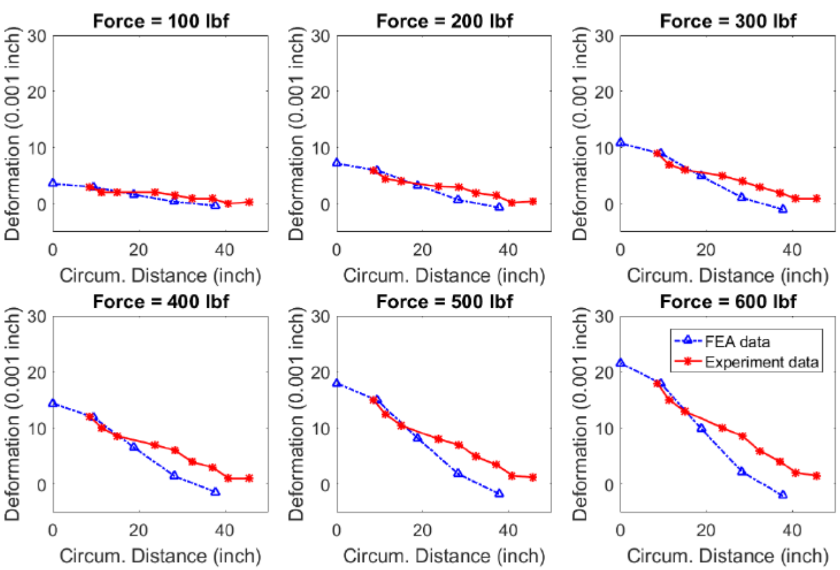
# Field Test: *Computer Model vs.. Physical Experiment*



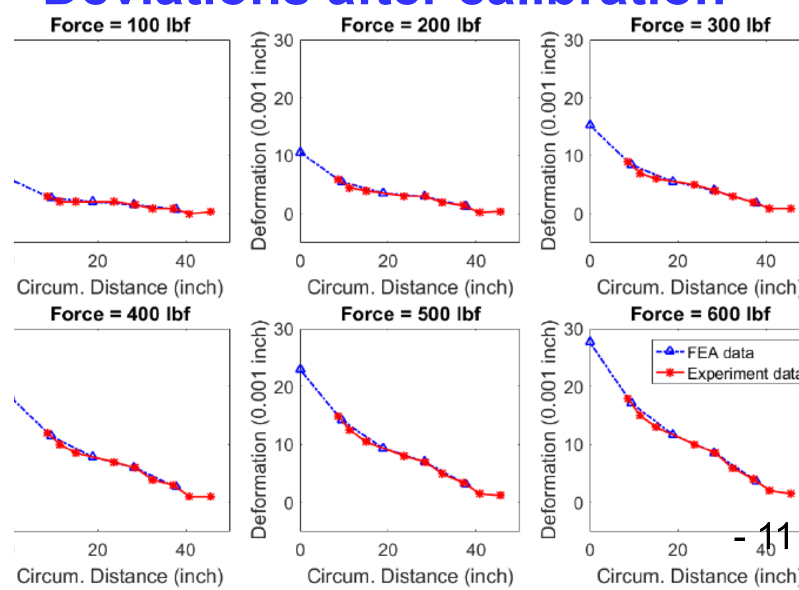



## Deviations without calibration



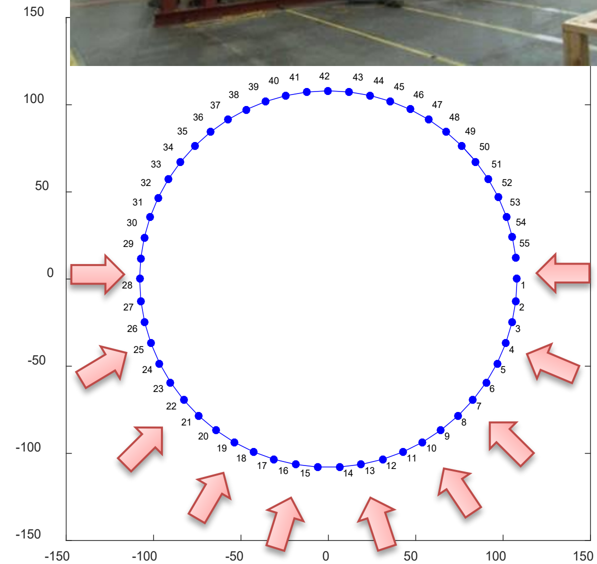

## Deviations after calibration

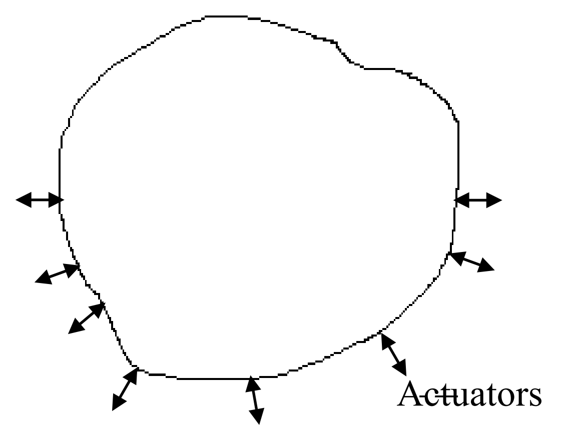


# Optimal Actuator Placement for Fuselage Shape Adjustment

- **Current Practice** (Yue, et al, 2018): **Actuators are placed in equal distance between two adjacent actuators**
  - **Limitations**
    - **Non-optimal**
    - **Larger actuator forces may be applied for some locations than needed**

- **Proposed Sparse Learning for Optimal Actuator Placement and Control** (Juan, et al, 2019)
    - **Considering incoming fuselage dimensions**
    - **Convex formulation**
    - **ADMM algorithm: Efficiently solved with global optimum**

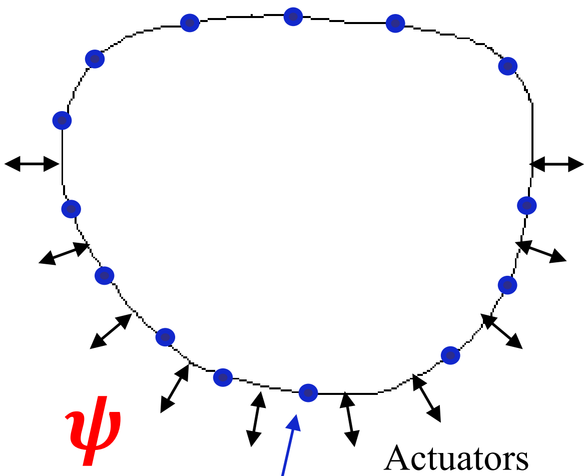




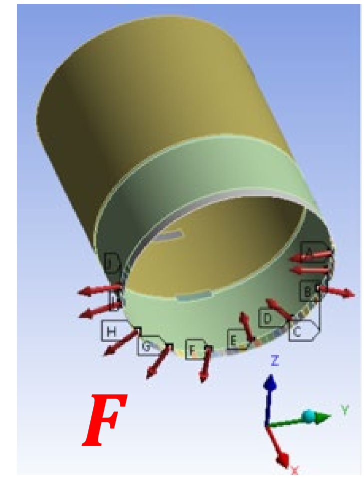
- Yue, X., Wen, Y., Hunt, J. H., Shi, J., 2018, "Surrogate Model-Based Control Considering Uncertainties for Composite Fuselage Assembly", *ASME Transactions, Journal of Manufacturing Science and Engineering*. Vol. 140, No. 4, 041017.
- Du, J., Yue, X., Hunt, J. H., and Shi, J. 2019." Optimal Placement of Actuators via Sparse Learning for Composite Fuselage Shape Control." *ASME Transactions, Journal of Manufacturing Science and Engineering*, Vol.141, No.10.pp1-37.

# Shape Control Problem Formulation




$n$ measured points


$m$ available actuator positions along the fuselage




Required $M$ actuators for adjustments $M < m$

**Output :** Weighted mean square of adjusted shape deviations (WMSD)

**Input :** Initial shape distortion $\boldsymbol{\psi} \in R^n$

**Input :** Weight matrix Positive diagonal $\boldsymbol{B} \in R^{n \times n}$

**Part Property:** Displacement Matrix $\boldsymbol{U} \in R^{n \times m}$

$$\min_{\boldsymbol{F}} \delta_{rms}^2 = \underbrace{(\boldsymbol{\psi} + \boldsymbol{U}\boldsymbol{F})}'\boldsymbol{B}(\boldsymbol{\psi} + \boldsymbol{U}\boldsymbol{F})$$

$$s.t.\ \|\boldsymbol{F}\|_0 = M,\ \boldsymbol{F}_L \preccurlyeq \boldsymbol{F} \preccurlyeq \boldsymbol{F}_Q$$

**Actuator force** $\boldsymbol{F} \in R^m$

**Sparsity requirement of** $\boldsymbol{F}$

**Deviations after shape adjustments**

**Safety requirement**

# Sparse Learning Modeling and Estimation

$$\min_{\boldsymbol{F}} L(\boldsymbol{F}) = (\boldsymbol{\psi} + \boldsymbol{UF})'\boldsymbol{B}(\boldsymbol{\psi} + \boldsymbol{UF}) \ + \lambda\|\boldsymbol{F}\|_1, \text{s.t. } \boldsymbol{F}_L \preccurlyeq \boldsymbol{F} \preccurlyeq \boldsymbol{F}_Q$$

- ***Proposition* 1. The ADMM** (alternating direction method of multipliers) **of the optimization problem can be derived as**

$$\boldsymbol{F}^{k+1} := \prod_C \left((2\boldsymbol{U}'\boldsymbol{B}\boldsymbol{U} + \rho\boldsymbol{I})^{-1}(\rho\boldsymbol{z}^k - \rho\boldsymbol{u}^k - 2\boldsymbol{U}'\boldsymbol{B}\boldsymbol{\psi})\right)$$

$$\boldsymbol{z}^{k+1} := S_{\lambda/\rho}(\boldsymbol{F}^{k+1} + \boldsymbol{u}^k)$$

$$\boldsymbol{u}^{k+1} := \boldsymbol{u}^k + \boldsymbol{F}^{k+1} - \boldsymbol{z}^{k+1}.$$

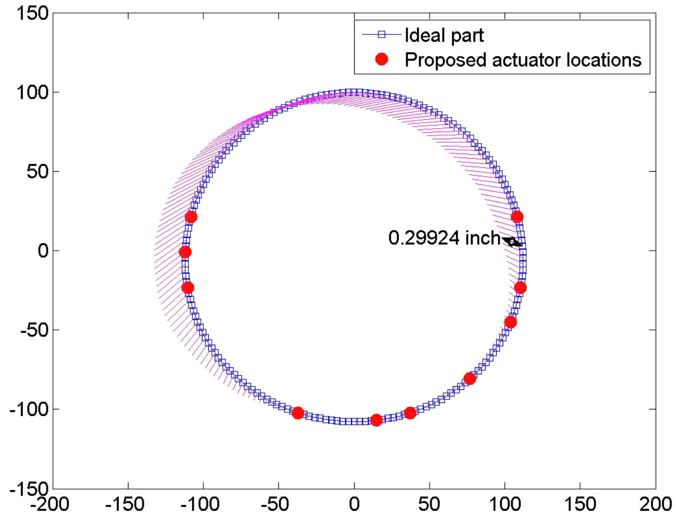
$\boldsymbol{I} \in R^{m\times m}$ is an identity matrix. $\prod_C$ is an Euclidean projection onto the convex set $C = \{\boldsymbol{F} \in R^m \colon \boldsymbol{F}_L \preccurlyeq \boldsymbol{F} \preccurlyeq \boldsymbol{F}_Q\}$, which can be denoted as

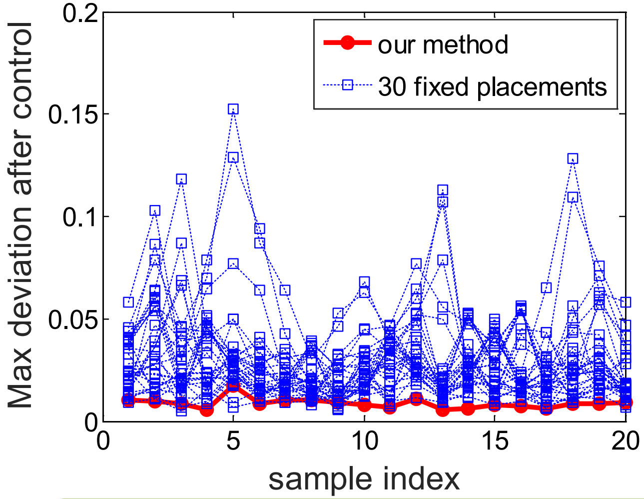
$$\prod_C(v) = \underset{\boldsymbol{F}\in C}{\operatorname{argmin}}(\|\boldsymbol{F} - \boldsymbol{v}\|_2)$$

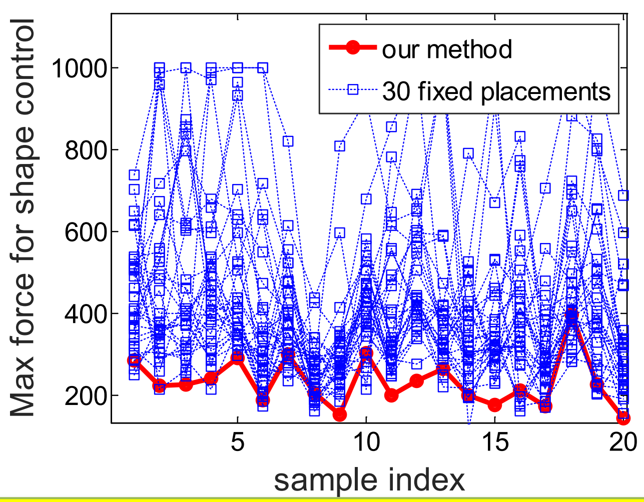
$S_{\lambda/\rho}(v) = (v - \lambda/\rho)_+ \ (-v - \lambda/\rho)_+$, where $(x)_+$ is short for $\max\{x, 0\}$.

# Comparison with Fixed Actuator Placement

- We randomly select $M$ actuators from $m$ feasible locations without replacements.
- 20 fuselages with 30 fixed actuator placements for each fuselages.
- Evaluation
  - Max deviations (MD) after shape control
  - Maximum force (MF) for shape control




| Method | Max Deviation (inch) | Max Force (lbf) |
|---|---|---|
| Sparse learning | **0.0083** | **175.25** |
| Current Practice | 0.0137 | 309.42 |

***Result: the optimal actuator placement uses less forces to achieve smaller shape deviations compared to the fixed actuator placements***

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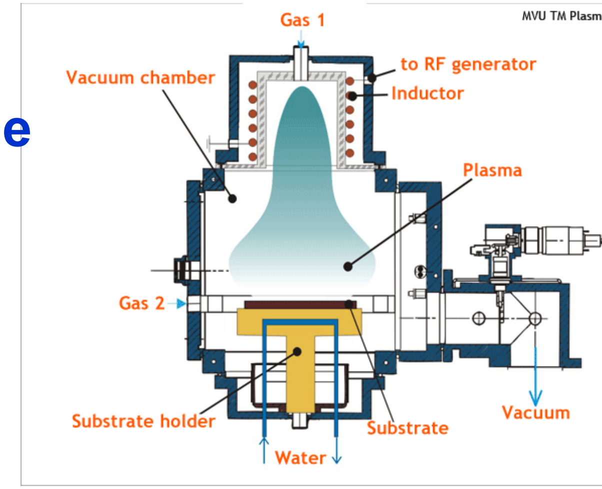
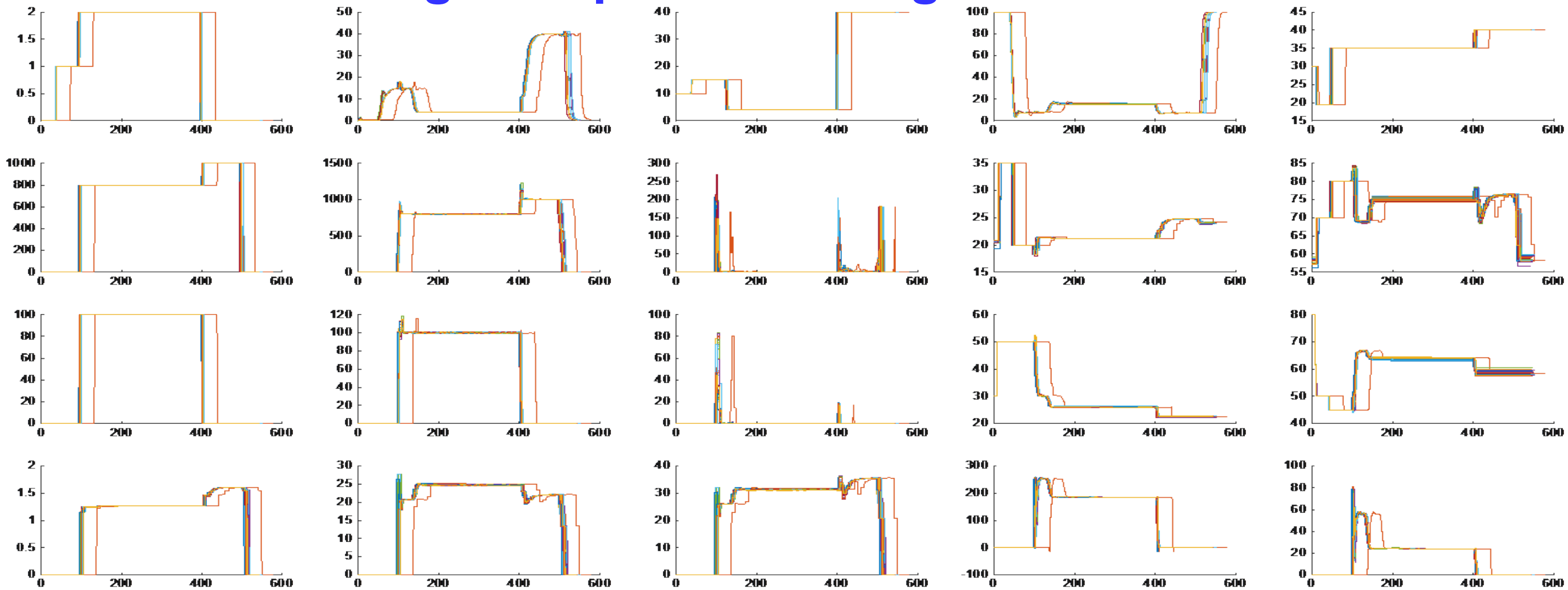
# Dynamic Multivariate Functional Data Modeling via Sparse Subspace Learning

**Challenges:**

- **Multiple profile (functional) data**
- **Multiple steps within each wafer fabrication cycle**
- **Each step has its own fabrication receipts, thus forms different correlation clusters among functional variables.**

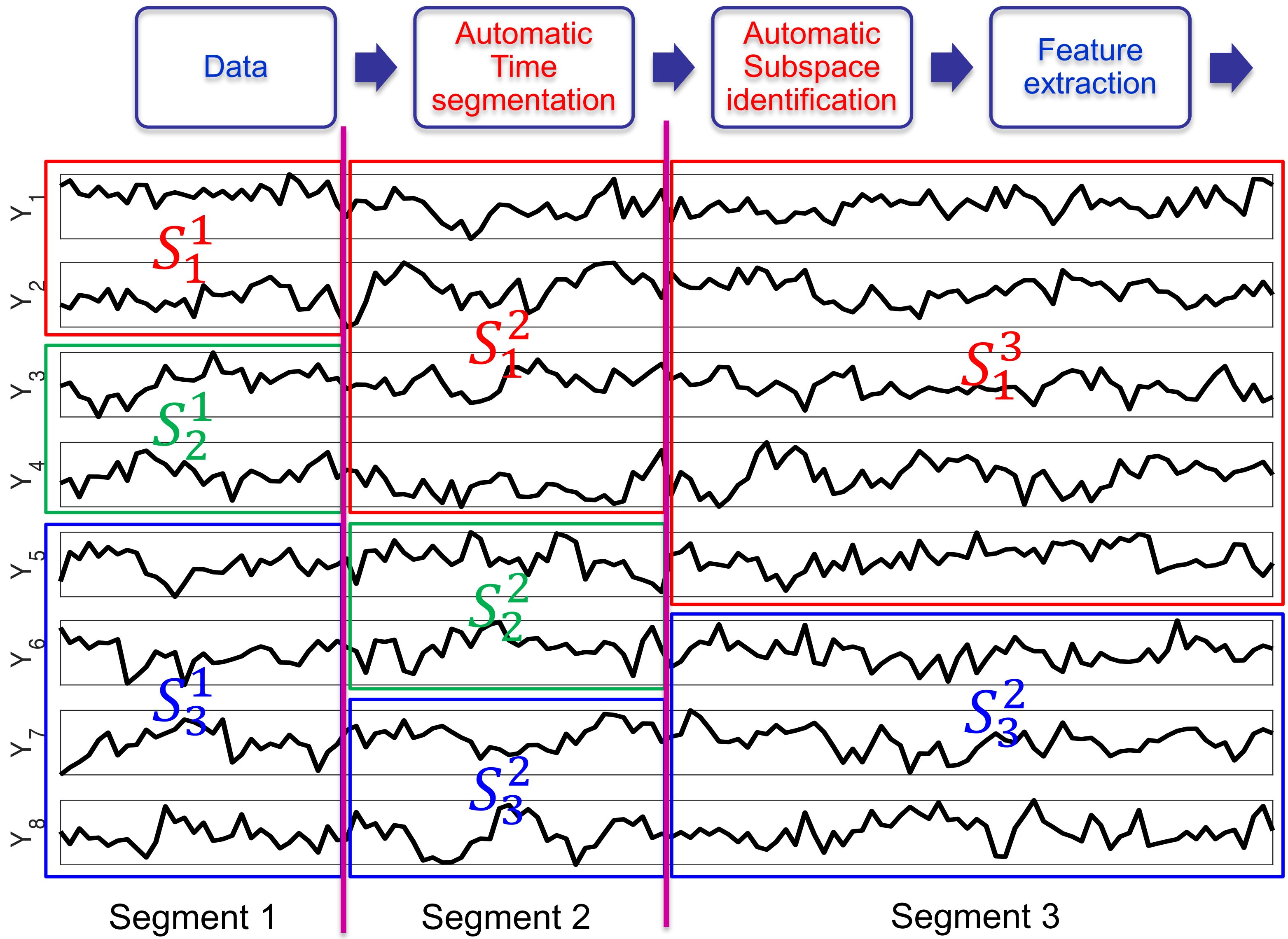



**Objectives:** **Unsupervised learning and anomaly detection combining multiple sensor signals**



Zhang, C., Yan, H., Lee, S., and Shi, J. (2020). [Dynamic Multivariate Functional Data Modeling via Sparse Subspace Learning](https://doi.org/10.1080/00401706.2020.1800516), *Technometrics*, (*2017 INFORMS Data Mining Section Best Paper Award*).
https://doi.org/10.1080/00401706.2020.1800516

# Objective:
# Automatic segmentation and Automatic clustering



# Subspace Representation and Subspace Clustering

## Self-expression Property

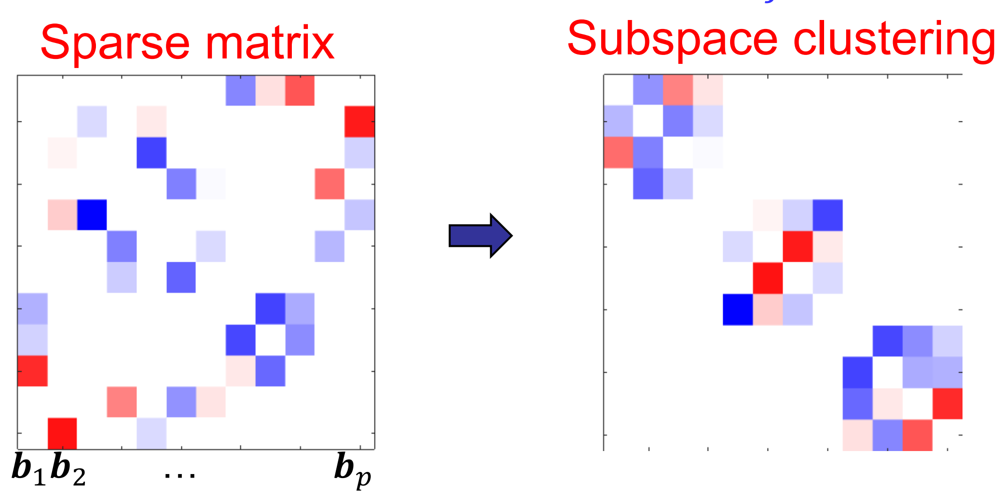
If the dimension of the subspace $S_l$, i.e., $d_l$, is smaller than the number of functions in it, i.e., $\rho_l$, and these functions are in general positions, then

$$X_j(t) = \sum_{X_r(t) \in S_l, r \neq j} b_{jr} X_r(t)$$

- $X_j(t), j = 1, \dots, p$, come from $L$ subspaces $S_l, l = 1, \dots, L$
- Regress one function $X_j(t)$ against other functions $X_r(t), r \neq j$

$$X_j(t) = \sum_{X_r \in S_l, r \neq j} b_{jr} X_r(t) + \sum_{X_r(t) \notin S_l} b_{jr} X_r(t)$$

- $b_{jr}$: partial cross-correlation between $X_j(t)$ and $X_r(t)$



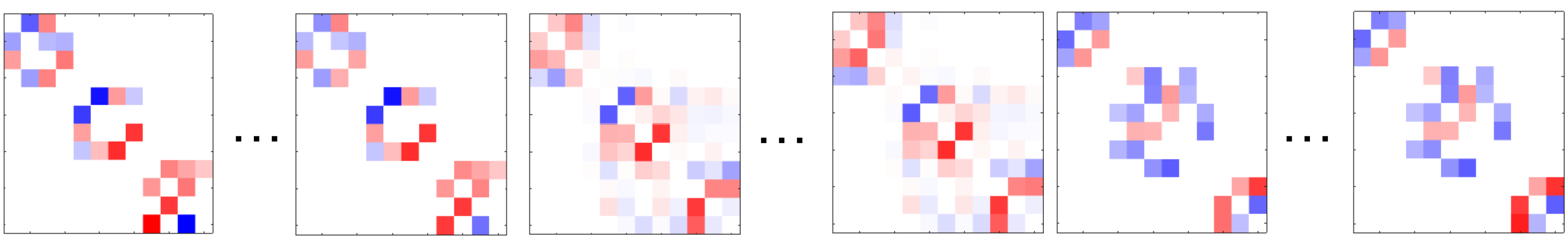

**Each block identifies one subspace**

# Dynamic Functional Subspace Learning

- Dependence structure of multivariate functions change over time
- $b_{jr}$ can change with time
- Regularize the change flexibility to avoid over-fitting

$$\min_{\boldsymbol{b}_{jr}(t), r\neq j, t=1,\dots,T} \boldsymbol{Z}_j' \boldsymbol{\Gamma}_j^{-1} \boldsymbol{Z}_j + \lambda_1 \sum_t ||\boldsymbol{b}_j(t)||_1 + \lambda_2 \sum_{r\neq j} \sum_t |b_{jr}(t) - b_{jr}(t-1)|$$

$$s.t. Z_j(t) = Y_j(t) - \sum_{r\neq j} Y_r(t) b_{jr}(t), \qquad b_{jj}(t) = 0, \qquad t = 1, \dots, T$$

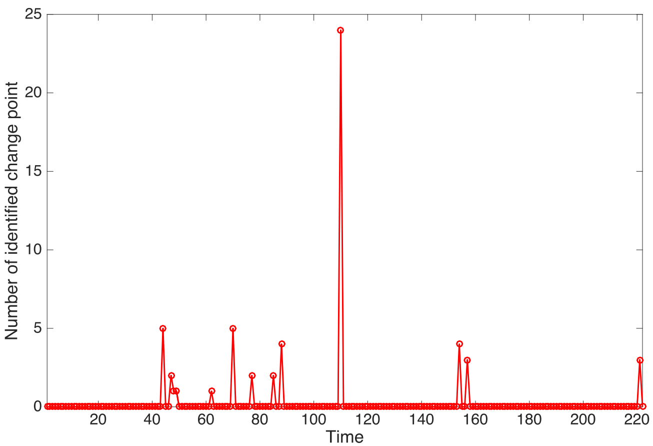


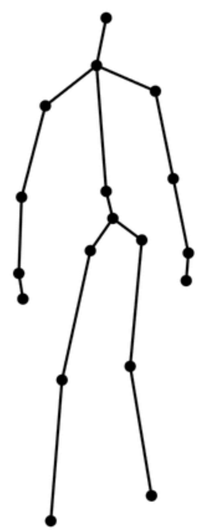
$t = 1$ … $t = 32$ $t = 33$ … $t = 60$ $t = 61$ … $t = 120$

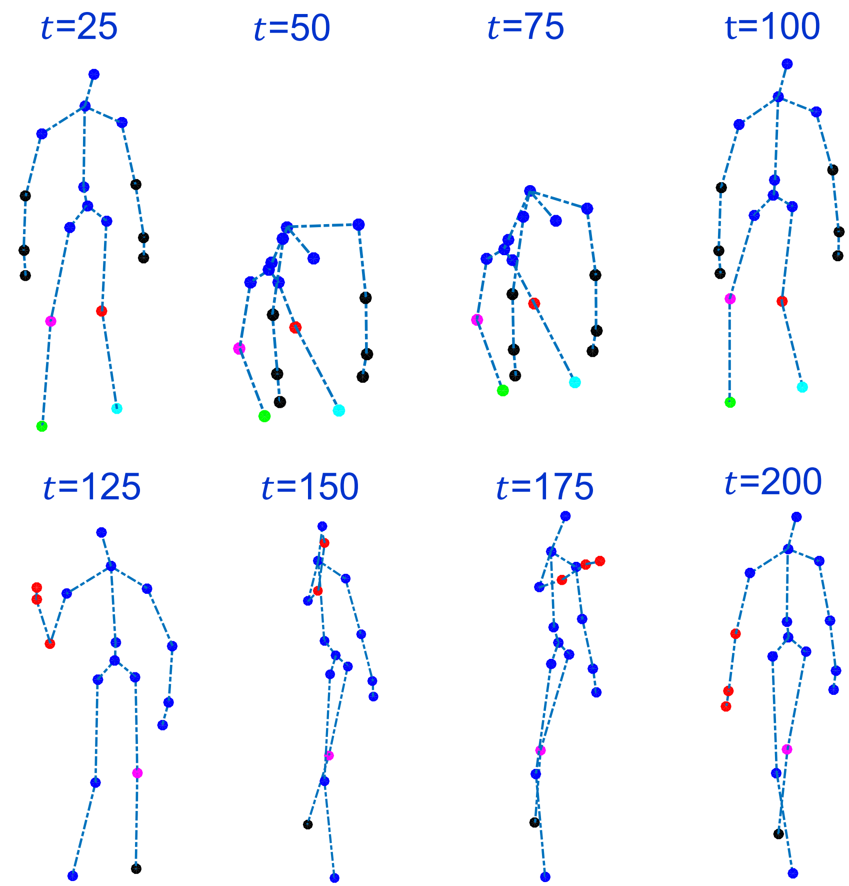
# Case Study: Human Motion Analysis

## Two gestures "bow up" and "throw"

- bow up: $t \in [1, 110]$
- throw: $t \in [111; 220]$






Dynamic subspace learning

Multichannel Functional Data → Automatic Time segmentation → Automatic Subspace identification → Feature extraction →

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# Our Recent Papers on ML Enabled Quality Improvements in Smart Mfg.

## Subspace Learning

- Zhang, C., Yan, H., Lee, S., and Shi, J.,2020. "Dynamic multivariate functional data modeling via sparse subspace learning. "*Technometrics*, 1-33.

## Active Learning

- Yue, X., Wen, Y., Hunt, J.H., Shi, J., (2020) " Active Learning for Gaussian Process considering Uncertainties, with an Application to Automatic Shape Control of Composite Fuselage", *IEEE* Transactions on Automation Science and Engineering, (accepted, in press).

## Matrix/Tensor Decomposition and Regression

- Yan, H.; Paynabar, K.; Shi, J. "Image-Based Process Monitoring Using Low-Rank Tensor Decomposition." IEEE Trans on Automation Science and Engineering 2015, 12 (1), 216–227.
- Reisi Gahrooei, M., Yan, H., Paynabar, K., Shi, J., 2020, "Multiple Tensor on Tensor Regression: An approach for modeling processes with heterogeneous sources of data", *Technometrics*, DOI: 1080/00401706.2019.1708463
- Wang, F., Reisi Gahrooei, M. , Zhong, Z., Tang, T., Shi, J. 2021. An Augmented Regression Model for Tensors with Missing Values. *IEEE Trans on Automation Sci and Eng*, under revision.
- Gahrooei, M. R., Paynabar, K., Pacella, M., & Shi, J. 2019. Process modeling and prediction with large number of high-dimensional variables using functional regression. *IEEE Transactions on Automation Science and Engineering*, 17(2), 684-696.
- Yue, X., Park, J. G., Liang, Z., Shi, J., (2020) "Tensor Mixed Effects Model with Application in Nanomanufacturing Inspection", Technometrics, 62(1), pp.116-129.
- Yue, X., Yan, H., Park, J. G., Liang, Z., Shi, J., (2018) "A Wavelet-based Penalized Mixed-Effects Decomposition for Multichannel Profile Monitoring based on In-line Raman Spectroscopy", IEEE Transactions on Automation Science and Engineering, 15(3), pp.1258-1271.
- Yue, X., Wen, Y., Hunt, J. H., Shi, J., (2018) "Surrogate Model based Control Considering Uncertainty for Composite Fuselage Assembly", ASME Transactions, Journal of Manufacturing Science and Engineering, 140(4), pp.041017-041017-13. doi: 10.1115/1.4038510.
- Miao, H., Wang, A., Li, B. and Shi, J. (2020) Reduced-rank Tensor Regression Model with Interaction Effects. Submitted to Journal of Quality Technology.
- Mou, S., Wang, A., Zhang, C., & Shi, J. (2020). Additive Tensor Decomposition Considering Structural Data Information. Submitted to IEEE Trans on Automation Science and Engineering.

## Bayesian Networks

- Li, J., and Shi, J., 2007, *"Knowledge Discovery from Observational Data for Process Control through Causal Bayesian Networks"*, *IIE Transactions*, Vol. 39, pp681-690.

## Machine Learning with Sparsity

- Yan, H., Paynabar, K., Shi, J. "*Anomaly Detection in Images With Smooth Background via Smooth-Sparse Decomposition*". *Technometrics* 2017, 59 (1), 102–114..
- Yan, H., Paynabar, K., Shi, J. "*Real-Time Monitoring of High-Dimensional Functional Data Streams via Spatio-Temporal Smooth Sparse Decomposition*", *Technometrics* 2018, 60 (2), 181–197.
- Du, J., Yue, X., Hunt, J. H., and Shi, J. 2019." Optimal Placement of Actuators via Sparse Learning for Composite Fuselage Shape Control." *Journal of Mfg Sci and Engineering*, Vol.141, No.10.pp1-37.
- Du, J., Cao, S., Hunt, J. H., Huo, X., and Shi, J., "Optimal Shape Control via L_infinity Loss for Composite Fuselage Assembly", *arXiv preprint arXiv:1911.03592*
- Wang, A., Du, J., Zhang, X., and Shi, J., " Ranking Features to Promote Diversity: An Approach Based on Sparse Distance Correlation", *Technometrics*, under revision. (2019 INFORMS Data Mining Section Best Paper Award Finalist)
- Wang, Y., Yue, X., Tuo, R., Hunt, J.H. and Shi, J., 2020. Effective model calibration via sensible variable identification and adjustment with application to composite fuselage simulation. Annals of Applied Statistics, 14(4), pp.1759-1776. （2017 INFORMS QSR Best Refereed Paper Award Finalist）
- Zhang, C.; Yan, H.; Lee, S.; Shi, J. "Weakly Correlated Profile Monitoring Based on Sparse Multi-Channel Functional Principal Component Analysis." *IISE Transactions* 2018, 50 (10), 878–891..

## Deep Learning

- Wang, F., Du, J., Zhao, Y., Tang, T., Shi, J., "A Deep Learning based Data Fusion Method for Degradation Modeling and Prognostics ", *IEEE Trans on Reliability*, in press, 2020.

## Multitask Learning

- Wang, A., & Shi, J. (2021). Holistic modeling and analysis of multistage manufacturing processes with sparse effective inputs and mixed profile outputs. *IISE Transactions*, *53*(5), 582-596.

## Dictionary Learning and Representation Learning

- Wang, A., Chang, T. and Shi, J. (2021) Multiple Event Identification and Characterization by Retrospective Analysis of Structured Data Streams. IISE Transactions. (under 2nd revision)

## Supervised Learning

- Du, J., Yan, H., Chang, T., and Shi, J., "A Tensor-Voting Based Surface Defect Classification Approach by Using 3D Point Cloud Data", *ASME Transactions, Journal of Manufacturing Science and Engineering*, under revision.

# Additional Information on Related Research Results

A seminar video on "Machine Learning Enabled In-Process Quality Improvements in Smart Manufacturing Systems" provides more discussions on Dr. Shi's related research ideas and results.

Video link:

https://www.youtube.com/watch?v=RUcYwXC0DlI&ab_channel=IMSEHKU

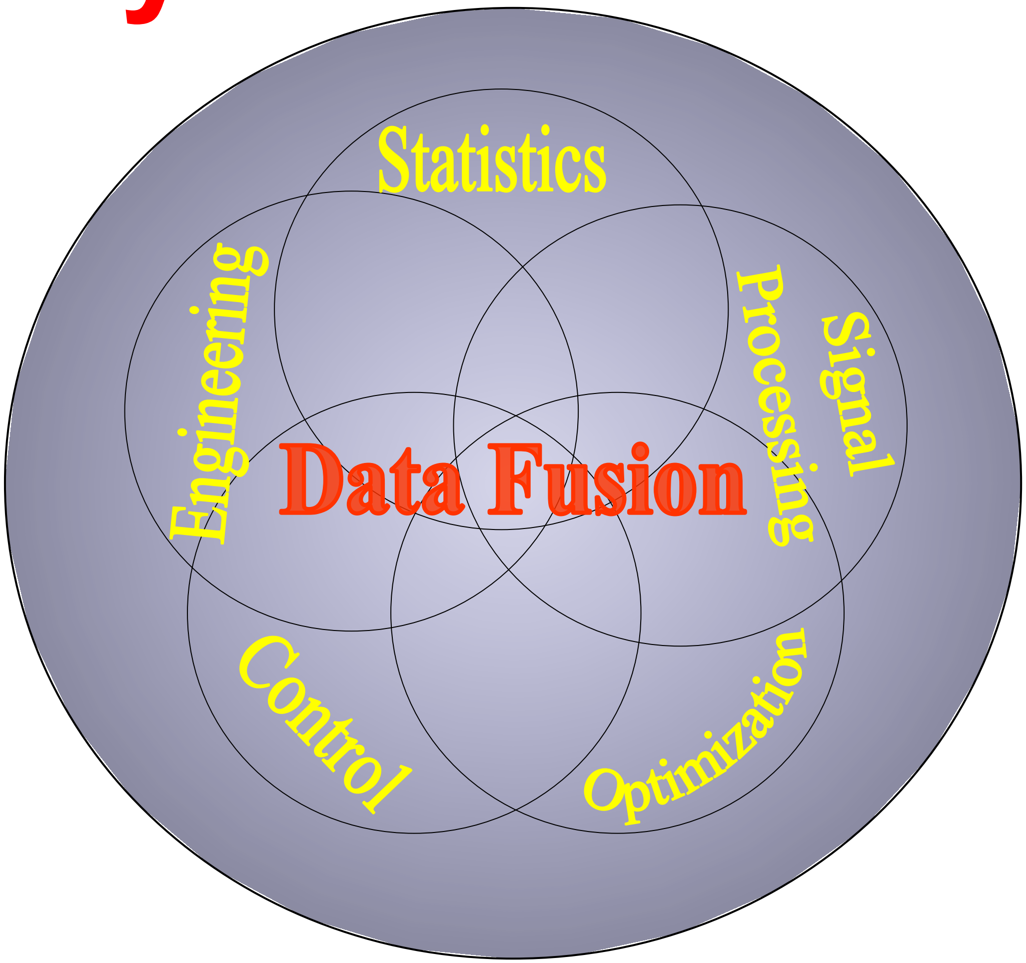
The talk starts with my understanding of smart manufacturing, followed by a review of the concepts and innovations of In-Process Quality Improvement (IPQI). The talk continues with a discussion on general procedures and key steps to conduct industrial data fusion, modeling, and analysis for accomplishing IPQI, illustrated by several real-life examples and case studies, providing insights on why certain IPQI tasks cannot be achieved without the ML methods. I hope the talk will benefit researchers, practitioners and graduate students who are interested in industrial data analytics, quality improvements, and machine learning applications.

The talk is based on my publications, which can be downloaded from this website: https://sites.gatech.edu/jianjun-shi/publications/

# Summary

- Smart Manufacturing provides new challenges and opportunities with a data rich environment for quality improvement.
- Machine Learning provides new tools and capabilities to enable quality improvements in data rich environment.
- Two examples are presented, which use machine learning methods to solve unsolvable problems in industry.
- There are much more research and implementation opportunities for quality improvements using machine learning in smart manufacturing systems.

# Thank you!


Statistics
Engineering
Signal Processing
Data Fusion
Control
Optimization