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

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

This talk focuses on Machine Learning Enabled Quality Improvement
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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

Advantage:
Reduce flow time; Increase productivity; Achieve high quality; Applicable to all part joins.
Sparse Learning and Model Calibration for Composite Fuselage Shape Control


FEA Simulation Platform and Validation

Material: Carbon fiber & Resin Epoxy

Fabrics

Stackups

Sub Laminates

Fabrication Process

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

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.

\[
\hat{\theta}_n = \arg\min_{\theta} L(Y^p, Y^s_\theta) + \lambda_n \| \theta - \theta_0 \|
\]

\[
= \arg\min_{\theta} (Y^p - Y^s_\theta)^T (\tau^2 \Phi_\theta + \sigma^2 I_n)^{-1} (Y^p - Y^s_\theta) + \lambda_n \sum_{i=1}^{m} |\theta_i - \theta_i^{(0)}|
\]

Field Test: Computer Model vs. Physical Experiment

**Deviations without calibration**

- Force = 100 lbf
- Force = 200 lbf
- Force = 300 lbf
- Force = 400 lbf
- Force = 500 lbf
- Force = 600 lbf

**Deviations after calibration**

- Force = 100 lbf
- Force = 200 lbf
- Force = 300 lbf
- Force = 400 lbf
- Force = 500 lbf
- Force = 600 lbf
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


Shape Control Problem Formulation

\[ \min_{F} \delta_{rms}^2 = (\psi + UF)'B(\psi + UF) \]

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

**Input:**
- Initial shape distortion \( \psi \in \mathbb{R}^n \)
- Weight matrix \( B \in \mathbb{R}^{n \times n} \)

**Part Property:**
Displacement Matrix \( U \in \mathbb{R}^{n \times m} \)

**Actuator force requirement**
\( F \in \mathbb{R}^m \)

**Sparsity requirement of** \( F \)

**Deviations after shape adjustments**

**Safety requirement**
\( F_L \leq F \leq F_Q \)

\( n \) measured points

\( m \) available actuator positions along the fuselage

Required \( M \) actuators for adjustments \( M < m \)
Sparse Learning Modeling and Estimation

\[
\min_{F} L(F) = (\psi + UF)'B(\psi + UF) + \lambda \|F\|_1, \text{ s. t. } F_L \preceq F \preceq F_Q
\]

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

\[
F^{k+1} = \Pi_C \left((2U'BU + \rho I)^{-1}(\rho z^k - \rho u^k - 2U'B\psi)\right)
\]

\[
z^{k+1} = S_{\lambda/\rho}(F^{k+1} + u^k)
\]

\[
u^{k+1} = \nu^k + F^{k+1} - z^{k+1}.
\]

\(I \in \mathbb{R}^{n \times n}\) is an identity matrix. \(\Pi_C\) is an Euclidean projection onto the convex set \(C = \{F \in \mathbb{R}^m : F_L \preceq F \preceq F_Q\}\), which can be denoted as

\[
\Pi_C(v) = \arg\min_{F \in C} (\|F - v\|_2)
\]

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

Evaluation
- Max deviations (MD) after shape control
- Maximum force (MF) for shape control

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

Objective:
Automatic segmentation and Automatic clustering

Data

Automatic Time segmentation

Automatic Subspace identification

Feature extraction

Segment 1 Segment 2 Segment 3
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

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

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

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

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

Sparse matrix Subspace clustering

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

$$
\min_{b_{jr}(t), r \neq j, t=1,...,T} Z_j^T \Gamma_j^{-1} Z_j + \lambda_1 \sum_t ||b_j(t)||_1 + \lambda_2 \sum_{r \neq j} \sum_t |b_{jr}(t) - b_{jr}(t-1)|
$$

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

Active Learning

Matrix/Tensor Decomposition and Regression

Bayesian Networks

Machine Learning with Sparsity
- 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)

Deep Learning

Multitask Learning

Dictionary Learning and Representation Learning

Supervised Learning
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=RUcYwXC0DII&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!