Change Detection in Precision Manufacturing Processes under Transient Conditions

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Outline

• Introduction of change detection in precision manufacturing processes
• Change detection in UPM & CMP
• DPGSM-based detection in sensor-based monitoring system during precision manufacturing
• Conclusions
Introduction

- **Ultra-Precision Machining (UPM)**

Ultra-precision machining are those technologies by which the highest possible dimensional accuracy is, or has been achieved (Taniguchi, 1983).
Introduction

• Challenges for UPM quality assurance
  – Limited metrology and methodology for quality control (Dornfeld, 2006)
  – Sensor-based in-process monitoring system of process monitoring and quality control (Abellan-Nebot, 2010)

Demand

• Suitable sensor based monitoring system for precision machining processes
• Effective incipient change detection analyzing weak signal of UPM compared with conventional machining processes
Surface defects in ultra-precision machining

Most common surface defects (e.g. surface scratches and variations) are due to abnormal vibration (e.g. chatters) and built-up edge (BUE)

- **System vibrations**
  - Chatter: tool, toolholder and spindle together vibrate at some natural frequency
  - Scratches on the surface, ruining the geometric acquirement of product

Rippled surface finish

Scratch
Surface defects in ultra-precision machining

- Built-up edge (BUE)
  - Causing deeper depth of cut and degrading surface finish
  - In UPM, surface sometimes rubs against built-up edge, leading to surface quality deterioration
CMP experiment setup

Buehler CMP machine

Wafer with nanometric roughness

XBee wireless sensor

Vibration signal
UPM experiment setup

- Sensor setup
  - Vibration sensor (3-axis)
  - Force sensor (3-axis)
  - Acoustic emission (AE) sensor

\[ Ra \sim 20 \text{ nm} \]

Scratch

Surface variation

Graph showing surface variation with Ra values of 150 nm and 900 nm.

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Application in ultra precision machining

- UPM experiment
  - Depth of cut (5, 10, 20, 25 μm)
  - RPM (500, 1000, 2000 rev/min)
  - Feed rate (1.5, 3, 6 mm/min)

SPC methods are reticent to intermittent pattern changes in UPM
DPGSM-based change detection in UPM

UPM & CMP Experiments
- Surface scratches
- Finish roughness variations
- In-process surface deterioration

Data acquisition

Feature extraction

Non-linear time series analysis

DPGSM-based change detection

DP-based Gaussian mixture

Transient behavior quantification

Weighted multivariate process control

Change detection

Decision for quality improvement

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Limitations of traditional detection methods

- Traditional statistical change detection involves testing a hypothesis
  - \( H_0: \theta = \theta_0 \) against \( H_1: \theta \neq \theta_0 \)
  - On parameters \( \theta \) of the distribution or a representation of a stochastic process, such as \( x(t+1) = f(x(t), \theta) \)

- For most detection methods, a stable operation implies stationarity, i.e., \( \theta \) is time-invariant

- However, most real-world processes are highly nonstationary, i.e., \( \theta \) varies over time
Limitations of traditional detection methods

• Autocorrelation structure change
  – Shifting trends (first order) (De Oca, 2010)
  – Volatility (second order) (Killick, 2013)
  – Eigenstructure of state space model (Basseville, 1987)

• Frequency and spectrum analysis
  – Spectral-based change detection (Choi et al., 2008)
  – Wavelet based control chart (Guo, 2012)

Few methods reported for change detection in transient processes because of the difficulty to capture the complex nonstationary behaviors
Intermittency is a common nonstationary (transient) behavior, consisting of intervals of regularity interrupted at random by bursts as the trajectory is re-injected into the chaotic part of the phase space.
Dirichlet Process-based Gaussian State Machines (DPGSM)

Reconstructed state space trajectories

Dirichlet process based transition matrix generation

Transition matrix 1

\[
\begin{bmatrix}
\pi_{11}^{(1)} & \cdots & \pi_{15}^{(1)} & \cdots & 0 \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
\pi_{51}^{(1)} & \cdots & \pi_{55}^{(1)} & \cdots & 0 \\
0 & \cdots & 0 & \cdots & 0
\end{bmatrix}
\]

Transition matrix 2

\[
\begin{bmatrix}
\pi_{11}^{(2)} & \cdots & \pi_{15}^{(2)} & \cdots & \pi_{18}^{(2)} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
\pi_{51}^{(2)} & \cdots & \pi_{55}^{(2)} & \cdots & \pi_{58}^{(2)} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
\pi_{81}^{(2)} & \pi_{85}^{(2)} & \cdots & \pi_{88}^{(2)}
\end{bmatrix}
\]
• **Chinese restaurant process**

\[
\frac{n_k}{\vartheta + n - 1} \quad \frac{\vartheta}{\vartheta + n - 1}
\]

Cluster 1  Cluster 2

- Tables represent infinite clusters
- Customer \( i \) represents data \( x_i \)

\[
P(c_i = k \leq C|c_{-i}) = \frac{n_k}{n-1+\vartheta} \quad \text{if data belongs to existing cluster}
\]

\[
P(c_i = C + 1|c_{-i}) = \frac{\vartheta}{n-1+\vartheta} \quad \text{if data belongs to new cluster}
\]
DPGSM change detection

Simulated Data

\[ \Pi^{(i)} = \{ \pi_{jk}^{(i)} \} = \begin{bmatrix} \pi_{11}^{(i)} & \cdots & \pi_{1K}^{(i)} \\ \vdots & \ddots & \vdots \\ \pi_{K1}^{(i)} & \cdots & \pi_{KK}^{(i)} \end{bmatrix}, \quad t_0 \leq i \leq T \]

Track the process change in terms of distribution of transition matrix

\[ (t_0 = 1000) \quad (T = 4000) \]
• Distribution of transition element
  
  – **Proposition 1:** The Bayesian posterior distribution of the vector $\pi_j$, given the counts $Z_j = z_j^{(i)}$ (multinomial distributed), follows a Dirichlet distribution

  \[
  f \left( \pi_j | z_j^{(i)} \right) = \frac{1}{B(z_j^{(i)})} \prod_{k=1}^{K} \pi_{jk}^{z_{jk}^{(i)} - 1}; \quad B \left( z_j^{(i)} \right) = \frac{\prod_{k=1}^{K} \Gamma(z_{jk}^{(i)})}{\Gamma\left( \sum_{k=1}^{K} z_{jk}^{(i)} \right)}
  \]

• Calculation of $z_j^{(i)}$

  \[
  z_{jk}^{(i)} = \sum_{t=i-L+1}^{i-1} P(c_t = j | x_t, \Theta) \times P(c_{t+1} = k | x_{t+1}, \Theta) + 1
  \]

  where \( P(c_t = k | x_t, \Theta) = b f(x_t | \theta_k) \), \( b \) is an appropriate normalized constant

  which makes \( \sum_{k=1}^{K} b f(x_t | \theta_k) = 1 \)
Multivariate control chart

• Confidential level
  – In DPGSM change detection, we have $K$ control charts ($K$ as cluster number)
  – $\alpha_j = 1 - (1 - \alpha) \frac{w_j}{K}$ is the significance level of row $j$, set by the family-wise error rate (FWER), i.e. $FWER = Pr(\text{rejecting at least one } H_j | H_j \in H_o) = \alpha$, where $H_o = \{H_1, H_2, \ldots H_K\}$

• Measurement in multivariate control chart
  – $\bar{\pi}_{jk} = \pi_{jk} | z_j^{(i)} = \frac{Z_{jk}^{(i)}}{\sum_{k=1}^{K} Z_{jk}^{(i)}}$
  – $d_j^2 = (\bar{\pi}_j - \pi_{j0}) S_j^{-1} (\bar{\pi}_j - \pi_{j0})^T \sim \chi^2_K$ distribution
Multivariate control chart

The overall on-line change detection, after consistent estimation of $\Theta$, \{$UCL_j$\} and $\alpha$ based on a training set, may be summarized as follows:

Step 1: Estimate transition matrix: 
$$\bar{\pi}_{jk} | z_{ij} = \frac{z_{jk}^{(i)}}{\sum_{k=1}^{K} z_{jk}^{(i)}}$$

Step 2: Calculate Hotelling statistics $d_j^2$ for each row $j$

Step 3: Monitor the process and estimate $ARL_1$ based on out-of-control points
**Benchmark case**

**Model:**

\[
x_i = \begin{cases} 
  f(x_{-i}; \varphi^{(1)}, \psi^{(1)}) & i_0 < i < i_1 \\
  \ldots & \\
  f(x_{-i}; \varphi^{(m)}, \psi^{(m)}) & i_{m-1} < i < i_m \\
  \ldots & \\
  f(x_{-i}; \varphi^{(M)}, \psi^{(M)}) & i_{M-1} < i < i_M 
\end{cases}
\]

where \( i_m \) is the time index of each breakpoint, \( m = 1, 2, \ldots, M, \ i_0 = 1, \ i_M = N \) (\( N \) is the length of the time series).

\( \{i_0, i_1, \ldots, i_m, \ldots, i_M\} \) as a sequence of order statistics such that each \( i_m \) follows a uniform distribution \( UNIF(0, N) \).

**ARMA(2,1) model** \( a_t \sim (N(0, \delta \sigma^2_a)) \)
Benchmark case

### ARL₁ comparisons (expected steps to reveal a change)

<table>
<thead>
<tr>
<th></th>
<th>EWMA</th>
<th>SD-WCUSUM</th>
<th>RNDP</th>
<th>DPGSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault A</td>
<td>25.6</td>
<td>2.2</td>
<td>6.1</td>
<td>3.5</td>
</tr>
<tr>
<td>Fault B</td>
<td>Inf</td>
<td>Inf</td>
<td>Inf</td>
<td>3.8</td>
</tr>
</tbody>
</table>
Detection for surface roughness variation

- Surface variation in three regions
  1. Small $Ra$ (~100nm)
  2. High $Ra$ (~150nm)
  3. High $Ra$ (~150nm) with larger variance

![Surface Roughness Boxplot](image)

**Scratch**

Region 1

Region 2

Region 3

**Surface Roughness Boxplot**

- DPGSM achieves consistently low ARL for detecting incipient surface quality variation within nano level.

- EWMA SD
- WCUSUM

**Expected delay of detection (ms)**

Region 1

Region 2

Region 3

- $10.4$  $1.5$  $0.5$
- $21.4$  $0.4$  $0.4$

**Region**

100
150
200 $Ra$ (nm)

Region

1 2 3
Detection for surface scratch

- Surface scratch and vibration signal
Detection for surface scratch

Expected delay of detection (ms) comparisons

<table>
<thead>
<tr>
<th></th>
<th>EWMA</th>
<th>SD-WCUSUM</th>
<th>DPGSM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>164</td>
<td>72</td>
<td>24</td>
</tr>
</tbody>
</table>

GP-DPGSM method discovers scratch appearance in 48 ms ahead of EWMA and 140 ms earlier than SD-WCUSUM.

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Change detection of surface deterioration

- Chemical Mechanical Planarization (CMP) process experiment
  - Lapped coppers \((Ra \ 10\text{nm} \sim 15\text{nm})\) were polished on Buehler in 3 minutes of each interval
  - Platen speed 250 RPM, head speed 60 RPM and download force 4 lbs

Buehler (model Automet® 250) with 3-axis accelerometer

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Change detection of surface deterioration

- Pad wear and surface deterioration
  - After 3 minutes, the average Ra improved to around 15 nm
  - Pad wear was then accelerated worn by soaking the pad in slurry, followed by air drying
  - After 12 minutes polishing, it was noticed that significant glazing of polishing pad observed (Fig. 2) as well as the scratch on wafer were observed and finish degrades to $Ra \approx 22$ nm
Change detection of surface deterioration

Delay for detection (ms)

<table>
<thead>
<tr>
<th>EWMA</th>
<th>SD-WCUSUM</th>
<th>DPGSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>2941</td>
<td>2262</td>
<td>34</td>
</tr>
</tbody>
</table>

DPGSM discovers surface deterioration with an order of magnitude (more than 2 sec) earlier than SPC methods tested.
Change detection for music pattern changes

• Case 1

Normal condition: \textbf{E5 to D5}  Key signature change

• Case 2

Normal condition: 1 1 1 2 2 2  
Anomaly condition: 1 1 2 2 1 2

<table>
<thead>
<tr>
<th>Comparison of delays for change detection (ms)</th>
<th>EWMA</th>
<th>SD-WCUSUM</th>
<th>DPGSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Key signature change</td>
<td>90</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Chord progression change in long period articulation</td>
<td>83</td>
<td>175</td>
<td>15</td>
</tr>
</tbody>
</table>

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Change detection 1: **Sequence change with ascending and descending scales**

Change detection 2: **Scale change with missing notes**

General types of Raga music

Subtle changes in intermittent music signals, namely scores sequence change and music scale change, are considered.
Change detection in Ragas

Ascending and descending scales

Scale change with missing notes

Comparison of delays for change detection (ms)

<table>
<thead>
<tr>
<th>Descending scale</th>
<th>EWMA</th>
<th>SD-WCUSUM</th>
<th>DPGSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ascending and descending scale</td>
<td>24 (False alarm)</td>
<td>Inf</td>
<td>17</td>
</tr>
<tr>
<td>Descending scale with missing note</td>
<td>1682</td>
<td>191</td>
<td>151</td>
</tr>
</tbody>
</table>
Detection of incipient sleep apnea

• Sleep apnea detection using ECG signal

Monitored ECG signal with incipient sleep apnea

Amplitude

Time Index

EWMA  SD-WCUSUM  DPGSM
1765  12  11

Delay for detection (ms) of sleep apnea

Normal Breathing  Blocked Airways

Nasal Cavity  Sinus cavities  Oral cavity  Hard Palate  Tongue  Epiglottis  Soft Palate  Uvula  Nasopharynx

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Conclusions

• We represent nonlinear nonstationary (intermittency) signal within precision machining processes as a **stochastic mixture of Gaussian clusters with Markov transition matrix**

• Intermittent changes in surface uniformity are efficiently identified by DPGSM, and it could detect surface damage (scratch) almost an order of magnitude earlier compared to existing change detection methods (EWMA and SD-WCUSUM)
Further studies

• Parameters selection
  – Selection of window length $L$ is crucial to derive consistent estimates of the transition matrix elements
  – Selection of the concentration parameter $\vartheta$ of Dirichlet process to ensure generation of proper Gaussian mixtures

• The transition process may be more closely approximated using a semi-Markov formulation and the representation needs to be modified to better capture the underlying dynamics
Q & A

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