Uncertainty Prediction for Tool Wear Condition Using Type-2 TSK Fuzzy Approach

Qun REN
Marek BALAZINSKI
Luc BARON
Outline

- Introduction
- Type-2 Takagi-Sugeno-Kang (TSK) fuzzy system and approach algorithm
- Tool conditions monitoring application
- Conclusions
Introduction (1)

- Tool condition has a strong influence on
  - surface finish of the workpiece;
  - dimensional integrity of the workpiece;
  - vibration levels of the machine tool.

- Cutting force components are most often used as tool wear symptoms

- Signal feature integration is necessary
Several different intelligence methods, which employ cutting forces for estimation tool wear, have been developed in the past few years; None of them can overcome the difficulty to estimate the errors of approximation during tool wear monitoring.
Aim

- to introduce the type-2 Takagi-Sugeno-Kang (TSK) fuzzy approach, incorporating a subtractive clustering method;
- to apply this innovative method to accomplish the integration of multi-sensor information into tool wear monitoring;
- to predict the uncertainties associated with the estimation process.
Type-2 TSK Fuzzy System

Type-1 TSK Fuzzy System

\[ x_{jk}^* = \left[ x_{jk}(1-a_j^k), x_{jk}(1+a_j^k) \right] \]

\[ p_j = \left[ p_j-s_j, p_j+s_j \right] \]
Type-2 TSK fuzzy approach
Tool Condition Monitoring System

Data Acquisition & Signal processing:
- filters, statistics
- FFT, RMS,...

Signal features

STRATEGY
- Process model, knowledge
- Diagnosis, command

ACTION!

sensors

Cutting zone

process variables
Experimental setup

- Dynamometer
- Charge amplifiers
- Connector block
- PCMCIA DAQ card
Cutting parameters

- **f**: feed rate (mm/rev)
- **t**: time (s)
- **v_c** (m/min):
  1: 351
  2: 417
  3: 251
  3: 251
  5: 300
  6: 300

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SNUN 120408
TiN - AL₂O₃ - TiCN coated sintered carbide

CSRPR 2525
Cutting forces measurements

Test W5

Test W7

IEEE SMC 2009, Oct. 11-14, 2009
Clusters obtained in the study

<table>
<thead>
<tr>
<th>Cluster</th>
<th>$f$ (mm)</th>
<th>$F_c$ (N)</th>
<th>$F_f$ (N)</th>
<th>$VB$(mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.47</td>
<td>1397</td>
<td>389</td>
<td>0.145</td>
</tr>
<tr>
<td>2</td>
<td>0.47</td>
<td>1413</td>
<td>431</td>
<td>0.156</td>
</tr>
<tr>
<td>3</td>
<td>0.33</td>
<td>1044</td>
<td>405</td>
<td>0.158</td>
</tr>
<tr>
<td>4</td>
<td>0.47</td>
<td>1395</td>
<td>372</td>
<td>0.130</td>
</tr>
<tr>
<td>5</td>
<td>0.33</td>
<td>1070</td>
<td>365</td>
<td>0.148</td>
</tr>
<tr>
<td>6</td>
<td>0.33</td>
<td>1112</td>
<td>423</td>
<td>0.158</td>
</tr>
<tr>
<td>7</td>
<td>0.47</td>
<td>1332</td>
<td>347</td>
<td>0.102</td>
</tr>
<tr>
<td>8</td>
<td>0.33</td>
<td>1032</td>
<td>334</td>
<td>0.113</td>
</tr>
<tr>
<td>9</td>
<td>0.47</td>
<td>1455</td>
<td>508</td>
<td>0.200</td>
</tr>
</tbody>
</table>

Nine cluster centers have been obtained by using subtractive clustering with the following parameters initialized:

$$r_a = 0.25, \quad \varepsilon = 0.60, \quad \bar{\varepsilon} = 1, \quad \eta = 0.15$$
Type-1 learning results based on W5
Type-1 testing results based on W7
Results from different AI methods

<table>
<thead>
<tr>
<th>AI method</th>
<th>Learning (W5)</th>
<th>Testing (W7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE (mm)</td>
<td>MAX (mm)</td>
</tr>
<tr>
<td>Neural Network</td>
<td>0.015</td>
<td>0.036</td>
</tr>
<tr>
<td>Mamdani FL</td>
<td>0.024</td>
<td>0.068</td>
</tr>
<tr>
<td>NF</td>
<td>0.014</td>
<td>0.030</td>
</tr>
<tr>
<td>TSK FL</td>
<td>0.006</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Summary of root-mean-square-error (RMSE) and maximum error (max) from the experimental results with different AI methods.
Type-2 learning results based on W5

Spreading percentages:

a = 11%;
b = 1%.
Type-2 testing results based on W7

Max diff: 0.000156mm;

Uncertainties:
Max: 0.479885mm;
Min: 0.000744mm.
Sources of Uncertainties

- Sudden changes of cutting parameters
  - six sets of cutting parameters
- Discontinuous input-output data sets
  - 10 cycles performed for learning experiment w5
  - 9 cycles performed for testing experiment w7
- Manual measurements
- Others
Conclusion (1)

- Type-2 TSK fuzzy approach
  - generates fuzzy rules directly from the input-output data acquired from sensors;
  - provides high accuracy and high reliability of the tool wear prediction over a range of cutting conditions;
  - interval set of output assesses the information of uncertainty in the estimation of tool wear condition.
The application of type-2 fuzzy logic on uncertainty prediction in machining has great meaning for continuous improvement in product quality, reliability and manufacturing efficiency in machining industry.
On-going and Future Research Direction

- Acoustic emission (AE) for tool condition monitoring;
- Tool life estimation;
- Integration of AE and cutting forces;
- High precision manufacturing – turning, micromilling, etc.
Thank You!

QUESTIONS

COMMENTS