A Novel Model for Tool-Wear Estimation

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**Aim:** To estimate wear in a milling tool from information present in the acoustic emissions during metal cutting.

**Data:** Samples from accelerometer mounted on tool spindle.

**Approach:** Model the wear process as a Hidden Markov Model.

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**Sound** - is affected by wear level.

- is an indicator of wear rate

**Three elements:**

- \( r(t) \) - Wear rate at time \( t \), is Markov.
- \( w(t) \) - Wear level at time \( t \).

\[
\begin{align*}
  w(t) &= w(0) + \sum r(t) \\
x(t) &= \text{Feature vector derived from the sound (observations)}
\end{align*}
\]

\[
x(t) \sim P_{\eta(t),w(t)}(x)
\]

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**Isolating wear-rate features**

1) Create classifier using only wear-level information.
2) Use classifier on training data to separate high-wear segments from low-wear segments.
3) Use Fischer discriminant to pick out features that most separate high-wear from low-wear.

**Average absolute wear error in 0.001 inch**

<table>
<thead>
<tr>
<th>Type of classifier</th>
<th>Training set</th>
<th>Testing set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Using wear-level information only.</td>
<td>0.46</td>
<td>0.42</td>
</tr>
<tr>
<td>Using wear-level and wear-rate information</td>
<td>0.33</td>
<td>0.37</td>
</tr>
</tbody>
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**Baum-Welch Algorithm:**

1) Start with a good guess for all parameters. (Transition probabilities and \( P_{\eta(t),w(t)}(x) \))
2) Take all sequences of \( r(t) \) that start from \( w(0) \) and end at \( w(T) \).
3) Compute expected values for parameters.
4) Iterate until convergence.