Multi-feature Fusion Based Tool Condition Monitoring in Rough Turning of Inconel 625

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Abstract:
Paper presents a tool wear monitoring strategy based on a large number of signal features in rough turning of Inconel 625. Signal features (SFs) were extracted from time domain signals, from frequency domain transforms and from their wavelet coefficients (time-frequency domain). All of them were automatically evaluated regarding their relevancy for tool wear monitoring based on determination coefficient between the feature and its low-pass filtered course, and their repeatability. The selected SF were used for tool wear was estimation. Accuracy of this estimation was then used for evaluation of sensors and signals usability.

Keywords: Cutting, Aerospace material, Tool condition monitoring, Signal feature extraction

1. Introduction
The search for process automation, stimulated by growing demands for higher quality and productivity, and reduction of human supervision of a machining process, resulted in the development of tool condition monitoring (TCM) systems. Tool wear is a relatively important problem when machining nickel-based heat resistant super alloys such as Inconel 625, which are employed in aeronautic and aerospace applications due to their high shear strength, work hardening tendency, highly abrasive carbide particles, tendency to weld and form a build-up edge, and low thermal conductivity [1]. All of these difficulties lead to high tool wear and compromise the attainment of high material removal rates. While machining Inconel 625, the cutting tool often bears extreme thermal and mechanical loads close to the cutting edge, leading to rapid tool wear. Therefore, the tool wear is not repeatable and has a tendency to finish catastrophically (chipping or breakage of the cutting edge). Hence, tool wear monitoring plays a critical role in guaranteeing the sustainable machining of nickel-based alloys. The development of a robust and reliable tool condition monitoring system requires the application of the most meaningful signal features (SFs), which best describe the tool wear [2,3,4]. Various methods for tool wear monitoring have been developed, most often based on cutting forces, acoustic emission (AE), and vibrations [2,5].

It is generally acknowledged, that it is not possible to make reliable process condition monitoring based on one signal feature (SF). Therefore, the key issue in TCM system is calculation numerous signal features correlated with tool and/or process condition [4,6-7]. The sensor signal has to be transformed into features that could describe the signal adequately and at the same time maintain the relevant information about tool conditions in the extracted features. There are several signal features (SFs) that can be extracted from any time domain signal, like average, effective value, variance, skewness, kurtosis etc. [6,7]. Sometimes signal is transformed into frequency or time-frequency domain (Fast Fourier Transform, Wavelet Transform etc), then signal features are extracted from these transforms. There can be many different descriptors from different sensor signals, most of them hardly related to monitoring process, therefore, a feature selection procedure is necessary. Relevant features, are then integrated into tool or process condition diagnosis.

The information extracted from one or several sensors’ signals has to be combined into one tool condition estimation. It can be achieved by various means, such as statistical methods, auto-regressive modeling, pattern recognition, expert systems and others [6,7]. The neural network approach has recently been the most intensively studied method for feature fusion [7]. Usually, a single neural network is used, where several SFs are fed into the network inputs, while the tool wear estimation is the network output. One of alternative approaches are hierarchical tool wear monitoring algorithms [4].

The objective of this paper is to compare usability of various signals and signal features originating from three sensors – cutting force, vibration and acoustic emission, applied for monitoring of tool condition while rough machining of Inconel 625. New algorithm of signal feature selection and elimination, and new system training was applied, based on data acquired in subsequent tool lives.

2. Experimental setup and conditions
The workpieces were impeller cases made of Inconel 625 (Fig. 1a), and machined with subsequent perpendicular cuts from diameter 406 to 268, with the depth of the cut $a_p = 2.5$ mm, feed $f = 0.2$ mm/rev, and cutting speed $v_c = 220$ m/min. The tool was a CRSNL with whisker-reinforced round ceramic inserts, RNN3 CC670 (Fig. 1a). Tool life was limited by three phenomena: tool notch wear (Fig. 1b), burr formation (Fig. 1c) and drastic increase in the surface finish (Fig. 1c). All three phenomena appeared autonomously, making the determination of the tool life end difficult, subjective, and dependant on the machine tool operator’s experience. Here, the used-up portion of the tool life ($\Delta t$), defined as.
the ratio of the cutting time as performed so far (t) to the overall tool life span (T), was used as the tool condition measure. Three workpieces were machined, during which seven tools were worn out. Higher number of used tools (tool lives) then machined workpieces is characteristic for machining of big, aerospace parts. Therefore application of TCM system is especially desirable.

The experiments were performed on a turning center TKX 50N equipped with an industrial AE sensor (Kistler 8152B121) and accelerometer (PCB PIEZOTRONICS 356A16) mounted on the turret and cutting force sensor (Kistler 9017B) mounted under the turret. A raw AE (AE<sub>raw</sub>) signal was acquired with a sampling frequency of 2 MHz using a DAQ card, NI PCI 6111. As this sampling frequency produces an enormously large amount of data, only 0.05 s (100,000 samples) out of every 10 s period was recorded and analyzed. Demodulated amplitude of AE signal (AE<sub>RMS</sub>), two cutting force signals (<i>F</i><sub>x</sub> and <i>F</i><sub>y</sub>) and two vibration signals (<i>V</i><sub>x</sub> and <i>V</i><sub>y</sub>) were acquired simultaneously with a sampling frequency 30 kHz using NI-PCI 6221 DAQ card at the same points of time during 1.66s (5000 samples each). Each cut lasted 96 seconds, during which eight such recordings of the signals were taken and treated as separate, subsequent measurements, used for tool wear monitoring.

![Figure 1](image1.png)  
Figure 1: Workpiece and tool (a), and tool life criteria: tool wear (b), burrs (c), surface roughness (d).

3. Signal processing

3.1 Signal feature extraction

As it really is not possible to predict, which signal features (SFs) will be useful in a particular case, as many as possible should be extracted from available signals, then those informative, correlated with tool wear should be selected for tool condition monitoring. Here, form each of 6 signals the five time domain SFs features were extracted: effective value (e.g. <i>F</i><sub>e,EVP</sub>), standard deviation (e.g. <i>F</i><sub>e,SD</sub>), skewness (e.g. <i>F</i><sub>e,Skew</sub>), kurtosis (e.g. <i>F</i><sub>e,Kurt</sub>), crest factor (the ratio of the peak level to the rms level, e.g. <i>F</i><sub>e,Crest</sub>). Fast Fourier Transform was applied to obtain eight frequency domain features: dominant frequency (e.g. <i>F</i><sub>e,PDB</sub>), power in dominant band (e.g. <i>F</i><sub>e,PDB</sub>), power in 6 selected bands (e.g. <i>F</i><sub>e,256-500</sub>). Finally, three level Wavelet Packet Transform (WPT) decomposition was used to obtain fourteen coefficients, called approximations A and details D, which are band pass signals (see Fig. 2). From each of these coefficients six time-frequency domain features were calculated: logarithmic energy (e.g. <i>F</i><sub>e,ADA</sub> is energy of wavelet coefficient ADA of signal <i>F</i><sub>e</sub>), skewness (e.g. <i>F</i><sub>e,ADA,Skew</sub>), kurtosis (e.g. <i>F</i><sub>e,ADA,Kurt</sub>), effective value (e.g. <i>F</i><sub>e,ADA,RMS</sub>), threshold crossing rate (number of times the signal crosses the threshold level, e.g. <i>F</i><sub>e,ADA,Count</sub>), and pulse width (the percentage of time during which the signal remains above this threshold e.g. <i>F</i><sub>e,ADA,Pulse</sub>), so there were 84 wavelet based SFs calculated from each signal.

Altogether there were 582 signal features calculated automatically, (97 from each of six available signals, 194 SFs from each sensor). Signals originating from each sensor were treated separately.

3.2 Signal feature selection

While number of extracted signal features is very large, some of them are very distorted, hardly dependant on tool wear (e.g. Fig. 3a), others are dependant mainly on the tool position on the workpiece (e.g. Fig. 3b). There are however SFs which are dependant on the tool condition (e.g. Fig. 3c) even if some depend also on the tool position (e.g. Fig. 3d). Only those SFs should be selected, which are relevant and sensitive to tool conditions.

To measure this relevancy, some model of relationship between the SF and tool wear or used up part of tool life dT is necessary. Here low-pass filtered signal feature was accepted as SF<sub>F</sub>(dT) model, which allowed avoiding any uncertain suppositions about mathematical formula of this model. As filter characteristic depends on number of elements in filtered time series, SF is first normalized in time to 0-100% of tool life (SF<sub>T</sub>), then SF<sub>T</sub> is filtered to SF<sub>T</sub>. Signal feature usability for tool condition monitoring can be evaluated using coefficient of determination R<sup>2</sup> which is a statistical measure of how well SF<sub>F</sub>(dT) model approximates the real SF<sub>F</sub>(dT) relationship, or – in other words – how much this model is better than just average value of SF<sub>T</sub>.
\[ R^2 = \frac{\sum (SF_{ji} - SF_{\text{avg}})^2 - \sum (SF_{ji} - SF_{avg})^2}{\sum (SF_{ji} - SF_{avg})^2} \]  

where:  
\[ \sum (SF_{ji} - SF_{avg})^2 \] - total square sum,  
\[ \sum (SF_{ji} - SF_{avg})^2 \] - residual square sum,  

\( SF_{avg} \) and \( SF_{avg} \) is a single value of \( SF_{i} \) and \( SF_{ji} \) respectively (\( i=0..100 \)), \( SF_{avg} \) is average value of \( SF_{i} \).  

On the other hand, selected SFs should not be strongly correlated one with each other to avoid multiplication of the same information. Therefore these SFs which meet the criterion, are then sorted into descending order, according to the \( R^2 \) values. Then the first (best) is selected and correlation coefficients \( r^2 \) between this SF and every other are calculated. SFs with \( r^2 > 0.8 \) are rejected as too much correlated with the best one. From among the remaining signal features, again the best one is selected, and the SFs correlated with it are rejected. The procedure is repeated until no signal feature meeting the \( R^2 > 0.4 \) criterion remains.

After completion of the second tool life, tool feature selection is repeated, using all available data, thus \( R^2 \) coefficients are calculated for both tool lives and averaged. Now application of second, even more important SF usability criterion can be applied: repeatability. It is evaluated using another determination coefficient \( R^2_r \):  
\[ R^2_r = \frac{\sum \sum (SF_{ji} - SF_{j_{avg}})^2 - \sum \sum (SF_{ji} - SF_{j_{avg}})^2}{\sum \sum (SF_{ji} - SF_{j_{avg}})^2} \]  

where \( SF_{j_{avg}} \) is the value of \( SF_{ji} \) in \( i \)-th point \( (i=0..100) \) and \( j \)-th tool life \( (j=1..2) \),  

\( SF_{j_{avg}} = \frac{1}{2} \sum_i SF_{ji} \) is average of \( SF_{ji} \) in \( i \)-th point  

\( SF_{j_{avg}} = \frac{1}{200} \sum_i \sum_j SF_{ji} \) is average of all \( SF_{ji} \) values in two tool lives.  

These SFs, for which \( R^2_r > 0.6 \) are assumed as repeatable enough. All SFs meeting both criteria are sorted according to the \( R^2 \) values. Elimination of SFs correlated one to each other is based on two tool lives data.

After the end of the third tool life, again whole SF selection and elimination procedure is repeated, using all available data. Figure 5 presents examples of signal features accepted by both criteria and recognized as correlated with the tool wear but not repeatable thus rejected.

Because the TCM system should be able to monitor the tool wear already after the first tool life, this evaluation is based on signals acquired during this first tool life. These SFs, for which \( R^2_r > 0.4 \) are assumed as satisfactory correlated with the tool condition. Figure 4 presents examples of SFs qualified and rejected by this criterion.

![Figure 3: Examples of signal features calculated from available signals during all 7 tool lives; skew of AEraw signal (a), kurtosis of \( F_x \) signal (b), energy of WPT coefficient ADD of \( V_y \) signal (c), and standard deviation of \( F_x \) signal (d).](image)

![Figure 4: Examples of SFs which met the \( R^2 > 0.4 \) criterion (a) and rejected by this criterion (b).](image)

![Figure 5: Examples of evaluation of signal features' repeatability based on data from three tool lives; SF which met the criterion (a), SF which was rejected as not repeatable, despite being correlated with tool wear (b).](image)
Signal features selected this way are used for tool wear monitoring in all subsequent tool lives, beginning from the fourth one. Thus signal features selected after each of three tool lives were different – see Table 1. As can be seen there, the force sensor produced the highest number of useful, relevant SF, meaning well correlated with tool condition, repeatable and not similar one to each other.

Table 1: Numbers of SFs selected from each sensor signals – number of all SFs meeting criteria $R^2 > 0.4$ and $R^2 > 0.6$ / number of SFs after elimination of similar SFs

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Force</th>
<th>Vibration</th>
<th>AE</th>
</tr>
</thead>
<tbody>
<tr>
<td>After 1st tool life</td>
<td>52 / 20</td>
<td>52 / 14</td>
<td>29 / 6</td>
</tr>
<tr>
<td>After 2 tool lives</td>
<td>31 / 18</td>
<td>44 / 14</td>
<td>33 / 7</td>
</tr>
<tr>
<td>After 3 tool lives</td>
<td>27 / 15</td>
<td>18 / 6</td>
<td>17 / 6</td>
</tr>
</tbody>
</table>

It must be stressed, that the signal features qualified after the first tool life does not have to be selected after two and three tool lives. E.g. the signal measures selected from accelerometer, sorted according to $R^2$ after 1st tool life and accordingly to $R^2$ after the 2nd and 3rd tool life were:

- after 1st tool life: $V_x$,$A$,$E$, $V_x$,$R$,$M$,$S$, $V_x$,$C$,$r$, $V_x$,$D$,$S$,$k$, $V_y$,$D$,$k$, $V_z$,$A$,$D$,$k$, $V_z$,$R$,$S$,$k$, $V_z$,$P$,$250$,$S$,$k$, $V_z$,$D$,$k$, $V_z$,$A$,$D$,$k$, $V_z$,$A$,$R$,$M$,
- after two tool lives: $V_x$,$C$,$r$, $V_x$,$S$,$D$,$k$, $V_x$,$D$,$P$,$u$, $V_x$,$A$,$D$,$k$, $V_x$,$R$,$M$,$S$, $V_y$,$P$,$4000$,$S$,$k$, $V_y$,$A$,$D$,$k$, $V_y$,$A$,$A$,$k$, $V_y$,$A$,$D$,$k$, $V_y$,$A$,$R$,$M$,
- after three tool lives: $V_y$,$D$,$P$,$u$, $V_y$,$A$,$A$,$D$,$k$, $V_y$,$R$,$M$,$S$, $V_z$,$P$,$4000$,$S$,$k$, $V_z$,$A$,$A$,$k$, $V_z$,$A$,$D$,$k$, $V_z$,$A$,$R$/$M$.

Interesting may be considering the possibility of using single signals separately and various combination of signals. Such comparison is presented in Table 2 (SFs numbers only after three tool lives). As can be seen there, number of useful signal features selected from two signals does not have to be the sum of the SF numbers selected from the signals separately, as the SF calculated from one sensor can be correlated to the SFs calculated from another signal. Data presented in Table 2 shows, that the cutting force component $F_x$ (perpendicular to the cutting speed vector) is source of more potentially useful SF than $F_y$ (parallel to the cutting speed vector) and vibration in direction $y$ is also more informative than parallel to the cutting speed. AE sensor produced the smallest number of useful signal features, from both – low and high frequency signals ($AE_{RMS}$ and $AE_{raw}$ respectively). All signals together produced 27 useful signal features, which looks promising.

As the cutting force sensor is much more difficult to install than the vibration and AE sensors installed on the surface of the machine tool, worth considering is using them both, without the cutting force sensor. Another option worth considering is resignation from $AE_{raw}$ signal, which requires much more demanding signal processing and separate DAQ device (high sampling frequency). This time in both cases number of SF useful for tool condition monitoring appeared to be sum of SF numbers obtained from separate signals.

Table 2: Numbers of SFs selected from various combination of signals after 3 tool lives - number of all SFs meeting criteria $R^2 > 0.4$ and $R^2 > 0.6$ / number of SFs after elimination of similar SFs

<table>
<thead>
<tr>
<th>$F_x$</th>
<th>$F_y$</th>
<th>$V_x$</th>
<th>$V_y$</th>
<th>$AE_{RMS}$</th>
<th>$AE_{raw}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>18 / 11</td>
<td>9 / 5</td>
<td>16 / 6</td>
<td>6 / 3</td>
<td>9 / 3</td>
<td>8 / 3</td>
</tr>
<tr>
<td>21 / 15</td>
<td>18 / 6</td>
<td>35 / 12</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>62 / 27</td>
<td>27 / 9</td>
<td></td>
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</tbody>
</table>

4. Decision making algorithm

Tool wear estimation is based on hierarchical algorithm [4]. In the first step of the algorithm the used-up portion of the tool life ($\Delta T$) is evaluated using every selected signal feature separately [8].

4.1. Tool condition estimation based on single signal feature

Here tool condition is estimated on the base on signal feature – used-up portion of tool live model in form of function $SF_{Tf}[\Delta T]$, which is an array of 101 elements (0-100% of $\Delta T$) - $SF_{Tf}[\Delta T]$.

![Figure 6: Used up portion of tool life evaluation based on single signal feature. a) search out in array $SF_{Tf}[\Delta T]$ for the value closest to $SF[n]$ obtained after last signal measurement; b) the search starts from previous result, thus $\Delta T$ value cannot diminish; c) the search limited to 30 elements of the $SF_{Tf}[\Delta T]$ array reduces influence of accidental high values; d) and enables to utilize non-monotonic the signal features.](image-url)
After subsequent signal measurement the system calculates signal feature value $SF[n]$, where $n$ is number of measurement (data acquisitions). Then $SF[n][\Delta T]$ array created after preceding tool lives are array, i.e. to 30 per cent of the tool life (see Fig. 6c). This means that, in the case of accelerated tool wear, the system allows three operations to be performed before it signals tool failure. This procedure also has another purpose, namely it enables signal features which are not monotonic with respect to the used-up portion of the tool life to be utilized, at least to some extent, as presented in Fig. 6d. In the example shown here, the signal feature value corresponds to $\Delta T=63\%$ and $\Delta T=95\%$. Restriction of the array search to 30 per cent of $\Delta T$ results indicates that $\Delta T=63\%$.

4.2. Integration of tool condition estimations

The integration of tool condition estimations based on each useful signal feature separately are integrated in the next step of the algorithm (Figure 7). All $\Delta T$ estimations are averaged and displayed as the final tool condition evaluation. This value is used as the initial value $\Delta T_n$ in the next iteration of algorithm (after next measurement).

Results of tool condition monitoring obtained for each sensor used separately and for all sensors used together are presented in Figure 8 as used-up portion of tool lives evaluated by the system $\Delta T_n$ versus actual values of $\Delta T$. As the first tool life was used only for system training, results of six following tool lives are presented there. The second tool (dashed line with circles) was monitored only on data gathered during the first tool life, the third tool (dashed line with triangles) was monitored on data from two first tool lives, while tools 4-7 (solid lines) were monitored using data from the tool lives 1-3.

Accuracy of tool condition monitoring evaluation can be assessed by using root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum (\Delta T_n - \Delta T)^2}$$ (3)

The $\Delta T$ values are expressed in percent, thus RMSE can be interpreted as average percentage errors. The RMSE errors are also presented in Figure 8.

As can be seen in Figure 8a, the best results (RMSE=8.7) were obtained while using cutting force sensor, which is not surprising – cutting force signals are commonly recognized as the most informative for tool condition monitoring. Here this signals produced the highest number of useful signal features (see Table 2). Results achieved by vibration sensor are relatively good (Figure 8b, RMSE=13.4), but much worse than obtained using the force sensor, which could be expected from lower number of useful signal features (Table 2). Not much worse were results based on AE signals (Figure 8c, RMSE=14.4) which produced similar number of good SFs. All signals used together (Figure 8d) produced results little worse than the force sensor alone, which means, that poorly repeatable AE signal features had negative influence on this result.

Figure 7: Hierarchical tool condition estimation.

Again it is worth considering the possibility of using single signals separately. Such comparison is presented in Table 3. If the force sensor measured only one ($F_1$ or $F_z$) component, the TCM system performance would be worse, than for both signals available, which is caused by the useful SFs numbers presented in Table 2. The $F_1$ signal alone produces much better result than $F_z$ signal, which is well known phenomena in tool condition monitoring. Vibration signals also allows for better tool wear estimation when used both than used separately, and direction perpendicular to cutting direction is more informative than parallel to cutting speed. Finally AE sensor which produces two signals in different frequency ranges ($AE_{rms}$ and $AE_{mix}$): when the signals were used separately each achieved some twice worse results (higher
RMSE) than cutting force signals, which is due very small useful SFs number. This time merging both signals allows the highest improvement of the result, making it only little worse than achieved using vibration signals. Application only vibration and AE sensors, much easier for installation than the cutting force sensor, results in RMS=12.5 which is better than achieved by the sensors separately. Resignation from $AE_{raw}$ signal, requiring much higher sampling frequency does not results in substantial worsening of the RMSE error.

![Image](attachment://image.jpg)

Figure 8: Used-up portion of tool life evaluated by the TCM system ($\Delta T_{aw}$) vs. actual portion ($\Delta T$) after training on selected signals.

Table 3: RMSE of tool wear monitoring based on various combination of signals

<table>
<thead>
<tr>
<th>$F_x$</th>
<th>$F_y$</th>
<th>$V_x$</th>
<th>$V_y$</th>
<th>$AE_{RMS}$</th>
<th>$AE_{raw}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>9.4</td>
<td>13.6</td>
<td>13.7</td>
<td>16.4</td>
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<td></td>
<td></td>
<td></td>
<td>12.5</td>
<td>12.9</td>
</tr>
</tbody>
</table>

5. Conclusions

Advance signal processing methods offers spacious number of possible signal features. It is impossible to predict in advance, which ones will be useful for tool condition monitoring in a particular application. Therefore efficient methods of their usability have to be applied. The methodology proposed here which was based on:

- modeling of the signal feature dependence on used-up portion of tool life by low pass filtering of the feature,
- qualification of SF usability by determination coefficient between the feature and its low pass filtered estimate and SF repeatability,
- elimination of similar (correlated one with each other) signal features,

proved its effectiveness in very difficult cutting conditions, where number of tool lives is less than number of machined parts. Tool condition monitoring strategy based on hierarchical algorithm was also tested and achieved results seem worth implementation in factory floor practice in aerospace industry.

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