Research Article

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In-Process Tool Wear Detection Using Internal Encoder Signals for Unmanned Robust Machining

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Abstract: Automated Tool Condition Monitoring (TCM) often relies on additional sensors sensitive to tool wear in order to achieve robust machining processes. The need of additional sensors could impede the implementation of tool monitoring systems in industry due to the cost and retrofitting difficulties. This paper has investigated the use of existing position encoder signals to monitor a special face turning process with constant feed per revolution and machining speed. A signal processing method by converting encoder signals into a complex-valued form and a new vibration signature extraction method based on phase function were developed to analyze the encoder signals in the frequency domain. The cumulative spectrum indicated that the spectral energy would shift from the lower to the higher frequency band with increasing cutting load. The embedded vibration signatures extracted from the encoder signals provided real-time detectability of the machining condition with distinguishable spectral modes. The embedded vibration signatures extracted from the encoder signals provided additional detectability of the machining condition with distinguishable spectral modes. In particular, tool chipping manifested itself as significant amplitude changes at a specific frequency band 20-30 Hz in the extracted vibration signatures. A new monitoring metric based on the XY-plane modulations combined with statistical process control charts was proposed. This metric was shown to be highly correlated to tool wear and tool wear rate. The results show that when tool chipping occurred, it could be detected when this tool wear rate value jumped in combination with breach of the control limits. This confirms that internal encoder signals, together with the proposed metric, could be an in-process tool wear monitor to help achieving unmanned robust machining.

Keywords: Face turning; TCM; tool wear; encoder signals; SPC; EWMA

1 Introduction

Tool wear, as a limiting factor in machining processes, is complex in the sense that it varies with the combination of tool-workpiece materials and machining conditions, which makes it quite challenging to detect and forecast. In an ideal situation, the cutting edges are subject to gradual wear during machining, until the end of tool life, specified by a maximum tool wear criterion. Excessive wear in short periods of time may drastically shorten the remaining tool life, leading to process failures and scrapped parts. Therefore, for increasingly important automated and unmanned machining, enabling of automated tool wear detection will play an ever important role in increasing the robustness of the machining process for cost effective production of high quality parts.

Automated Tool Condition Monitoring (TCM) relies on the use of relevant signals and appropriate numerical methods for the extraction of signal features sensitive to tool wear, followed by a classification of the condition of the cutting tool based on the most reliable features. Various approaches towards automated tool wear and tool breakage detection, including the choice of signals and feature extraction methods, have been extensively studied over the past several decades [1–4].

Typically, the tool wear is detected by measuring the changes in the dynamics of the machining process. Common sensors used for tool wear detection include force sensors, such as table-mounted or spindle-integrated dynamometers, multi-axis accelerometers mounted on the workpiece or tool holder, acoustic emission sensors mounted on the workpiece, etc.

An effective tool wear detection method was developed by Jan Jeppsson at Boeing [5]. In Jeppsson's ap-
proach, it was observed that the radial cutting force increases substantially when flank wear is developed while the tangential cutting force remains relatively unchanged. As a result, the ratio of the radial force over the tangential force would increase sensitively even at small amount of tool wear. One consequence of this tool wear phenomenon is that the radial force in milling passes through the center of the spindle, resulting in no additional cutting torque. As a result, spindle current is not an effective signal for detecting flank wear in milling. The phenomenon could be explained by the Orthogonal Cutting Model (OCM). Due to the flank wear, the contact area between the tool and the workpiece gradually increases during the cut resulting in a higher radial force due to the higher normal contact stress between the flank surface of the tool and the workpiece.

1.1 Position encoder signals for tool wear detection

The need of additional sensors often impedes the implementation of tool monitoring systems in industry. For some machining processes, especially in very harsh machining conditions as shown in Fig. 1, mounting and use of additional sensors could be challenging and potentially comprimise the robustness of the machining process.

![Figure 1](image)

**Figure 1:** Harsh industrial machining condition with an accelerating work table and jets of cutting fluids, from a machine tool operator’s viewpoint.

Existing sensors, such as the position encoders of the machine tool could be a viable approach to monitor the state of the cutting process, for an easier implementation and without the additional cost of sensors. The advantages with existing sensors include reduced cost, avoiding retrofitting difficulties without adding to the overall complexity of the machining system.

The responses from linear encoders may contain vibration signatures from various excitation sources. For example, the lower frequency components which are often related to the machine tool’s structural components when heavy masses, such as tables and columns, are carried at high velocities. The tool-workpiece interaction can also excite the structural components of the machine tool. The characteristic process frequencies, such as the cutter- and tooth-passing frequencies, can, therefore, also be expected in the encoder signals.

A series of unbalance tests were conducted in [6] on the turn table of a machine tool, which confirmed a variation in the encoder responses due to varying size of the unbalance. This study clearly showed that encoders are highly sensitive to the vibrations due to periodic excitation of the machine tool structure, even though no cutting process was involved.

Girardin et al. [7] showed that the variations in the spindle’s angular velocity can be used to detect critical tool wear and the genesis of tooth breakage in a single-tooth down-milling process. A slow-down of the spindle speed due to increasing spindle torque was observed. A part of their analysis was carried out in the frequency domain and they concluded that it is sufficient to monitor the operational frequencies, i.e. the cutter frequency and tooth-passing frequency, for the detection of tooth breakage.

In another work [8], the vibration signature in the encoder signal due to the periodic excitation force in milling was investigated. The methodology of applying phase space analysis to encoder signals was presented. A phase space reconstruction of the milling dynamics was carried out by embedding the modulation component in the position signal in the feed direction. It was found that the dynamics represented by the modulation signal in that particular application was non-chaotic and could fully be resolved in a higher dimensional embedding space.

The past research on using internal position encoders of the machine tool for machining process monitoring has indicated that both linear and rotary encoders are potentially good signal sources, admitting extraction of information related to the condition of the machining process, such as the tool-workpiece interaction, tool wear and tool breakage.

1.2 Difficulties in using encoders for process monitoring

The output signals from position encoders have a relatively high dynamic range which makes them highly usable for
analyzing forced vibrations which are regarded as non-severe. The encoder signals are in general non-stationary and therefore requires non-linear signal analysis methods to extract the useful components from the signals.

In this paper, the fundamental nature of encoder signals is investigated by removing the varying factors introduced by the milling process. Instead, a face turning experiment is designed to make the machining process quasi-static so that the vibration due to the cutting can be distinguished from the encoder signals.

This paper is organized as follows: In Section 2, a special face turning process is designed to achieve a constant feed per revolution and cutting speed. The theory of encoder signal processing is then presented. The experimental setup is described in Section 3, followed by the results and discussion in Section 4 with final concluding remarks given in Section 5.

2 Face turning process monitoring

A special face turning process is set up on a 5-axis machine to maintain a constant feed per revolution and a constant cutting speed for process monitoring. This design renders the face turning process consistent with the OCM with constant uncut chip thickness and machining speed, thus, a quasi-static process. The process starts from the initial diameter $D_0$ to the final diameter $D_1$, while the feed rate and rotational speed are controlled to maintain a constant cutting speed and feed per revolution as shown in Fig. 2. The vertical depth of cut can be altered to change the cutting condition while keeping the feed per revolution and cutting speed the same. For this process, the following three cutting stages are defined:

1. An initial stage when the cutter first engages the workpiece until the feed per revolution $f$ reaches the desired value. This stage lasts for approximately 1.4 seconds.
2. A quasi-steady stage when $f$ is near constant.
3. A final stage $f$ gradually decreases to zero. This stage lasts for approximately 0.3 seconds.

The linear path of the actual cutting point is directed towards the centre of rotation. The trajectory traced out on the generated surface is an Archimedean spiral with a constant pitch defined by the feed per revolution, which is equivalent to the uncut chip thickness according to the OCM. In order to maintain a constant cutting speed $v_c$, the rotational speed $n(t)$ of the work table needs to increase as the final diameter is approaching as given by the relation

$$n(t) = \frac{10^3 v_c}{\pi d(t)}$$

It can be shown that the instantaneous diameter $d(t)$ is given by

$$d(t) = \sqrt{D_0^2 - \frac{4 \cdot 10^3 v_c f}{\pi} t}$$

where $t$ is the time into the cut (in minutes).

The feed rate of the cutter towards the centre of rotation is also gradually increased as it is synchronized with the rotational speed of the work table, as given by

$$v_f(t) = fn(t)$$

It can be shown that the total effective cutting time (in minutes) for this particular face turning process is given by

$$t_c = \frac{\pi (D_0^2 - D_1^2)}{4 \cdot 10^3 v_c f}, \quad D_0 > D_1$$

With this process setup, we explore the use of the encoder signals for process monitoring to distinguish changes in different machining conditions.

2.1 Complex form of position encoder signals

Let $s(t)$ denote a general real-valued time signal. The corresponding analytic signal, which is complex-valued, is
then defined as \( z(t) = s(t) + jH\{s(t)\} \) where \( H\{\cdot\} \) is the Hilbert Transform (HT) of \( s(t) \). The HT as such, is found to be a useful operator for the evaluation of the instantaneous properties, such as the instantaneous amplitude and phase of the signal [9]. For example, a simple transform is \( H\{\cos t\} = \sin t \). A general mathematical description of the differentially measured output signals from sinusoidal linear (or angular) position encoders, assuming a constant amplitude, is

\[
\begin{align*}
  u_A(t) &= A \cos \theta(t) \\
  u_B(t) &= A \sin \theta(t)
\end{align*}
\]

These encoder signals can be combined and expressed in a complex exponential form as

\[
z(t) = u_A(t) + ju_B(t) = a(t) e^{j\theta(t)}
\]

where \( a(t) = \sqrt {u_A^2(t) + u_B^2(t)} \) is the instantaneous amplitude and \( \theta(t) = \text{arg} \, z(t) \) is the instantaneous phase function. Here, \( u_A(t) \) and \( u_B(t) \) are the differentially measured quadrature signals from the encoder pins usually denoted by \( \pm A \) and \( \pm B \) respectively. These signals are phase-shifted by 90° by their definition. The direction of the motion is given by the sign of the phase difference between these signals. In the positive direction \( u_A(t) \) is ahead of \( u_B(t) \) and vice versa when travelling in the negative direction. Note that the complex-valued signal in (6) represents an ideal analytic encoder signal since \( H\{u_A(t)\} = u_B(t) \). The main characteristic of such analytic signals is that the spectral amplitudes at the negative frequencies in \( u_A(t) \) and \( u_B(t) \) are cancelled out while doubling the magnitudes for the positive frequencies. This can be observed by taking the Fourier Transform (FT) of the analytic signal \( z(t) \).

### 2.2 Instantaneous phase function

The instantaneous phase function \( \theta(t) \) may contain a carrier phase component \( \theta_c(t) \) and a phase modulation component \( \Delta \theta(t) \) and is defined as

\[
\theta(t) = \text{arg} \, z(t) = \tan^{-1} \left( \frac{u_B(t)}{u_A(t)} \right) = \theta_c(t) + \Delta \theta(t)
\]

Signal noise may also be present in the phase function but has been left out from the above signal model. The instantaneous carrier frequency \( \omega_c(t) \) will be a time-varying function and directly proportional to the instantaneous feed speed defined in (3).

\[
\omega_c(t) = 2\pi \frac{v_f(t)}{60} M_L
\]

where \( M_L \) denotes the resolution of the linear encoder specified as the number of cycles of the sinusoidal wave per millimeter movement. The instantaneous carrier phase is related to \( \omega_c(t) \) by the integral

\[
\theta_c(t) = \int_0^t \omega_c(\tau) \, d\tau
\]

The relation between the instantaneous phase and the instantaneous position signal \( x(t) \) is therefore given by

\[
\theta(t) = 2\pi M_L x(t)
\]

where \( x(t) \) is the encoder signal along the X-axis. It needs to be pointed out that in the following derivations, \( x(t) \) can be substituted to e.g. \( y(t) \) when the position encoder of a different axis is considered.

### 2.3 Embedded vibration signatures

It must also be pointed out that, in the face turning process presented in this work, the position signal \( x(t) \) contains both the nominal tool path towards the centre of rotation plus the induced vibrations from the machining process which is to be analyzed. The process-related vibrations are picked up by the highly sensitive position encoders which will modulate the carrier frequency \( \omega_c(t) \) and thus reflecting the on-going speed fluctuations along the machine axis.

Given that the encoder signals are properly sampled by following the Nyquist sampling theorem, the modulating component of the signal can be recovered by performing a phase demodulation. This is a time-domain operation which will down-shift the complex-valued signal \( z(t) \) in frequency by the amount specified by the carrier phase function in (9). The resulting frequency-decimated signal \( z_d(t) \), which is also complex-valued, is then given by

\[
z_d(t) = z(t) e^{-j\theta_c(t)} = a_d(t) e^{j\Delta \theta(t)}
\]

where \( a_d(t) \) is the instantaneous amplitude of the demodulated encoder signal and \( \Delta \theta(t) \) is the phase modulation component of the original phase function found in (7). The overlaid process-related vibration signal, properly scaled from electrical angle into the corresponding spatial unit, is then obtained as

\[
\Delta x(t) = \frac{1}{2\pi M_L} \Delta \theta(t) = \frac{1}{2\pi M_L} \text{arg} \, z_d(t)
\]

Note that this technique to isolate the modulating component of the signal requires that the true instantaneous carrier phase \( \theta_c(t) \), which is given by the integral of
the instantaneous feed rate $v_f(t)$ according to (8) and (9), is known in advance. In general, this is not the case in actual machining tests due to signal noise and uncertainties related to the control action of the machine tool. Another problem is that the exact start and stop of the machining is difficult to measure with indirect methods when outside the cutting process. Hence, even small uncertainties in the carrier frequency could result in unwanted trends, possibly non-linear, in the recovered modulation signal, which may require additional signal preprocessing to fully utilize the process-related information contained in the modulation signal for process monitoring tasks. In this work, we adopt a modelling approach to accurately perform the off-line demodulation which is presented in the following subsection.

2.4 Off-line signal demodulation and synchronization

As shown in Fig. 2, the feed axis is defined as the $Y$-direction. It must be pointed out that no general method exists to detect the start and end of the cut. The $Y$-offset and time offsets in the measured feed axis position signal ($Y$) will also be different between the experiments due to the rapid internal feed speeds, resulting in sinusoidal frequencies above the critical Nyquist frequency and lost tracking of the relative position along the feed axis. During the cut, the feed rate is gradually increased and the position tracking is not distorted by any aliasing effects. Given that the origin is defined at the centre of the rotation, based on (2), the feed axis position $\hat{y}(t)$ during the cut, can be modelled as

$$\hat{y}(t) = m + \frac{1}{2} \sqrt{D_0^2 - \frac{4 \cdot 10^5 v_c f}{\pi}} \cdot \frac{(t - \tau)}{60} \quad (13)$$

where $m$ denotes the $Y$-offset (in millimeters) and $\tau$ is the time offset (in seconds). These signal offsets can be found by e.g. the least squares fit of (13) to the $Y$-axis position samples by solving the minimization problem

$$\arg \min_{m, \tau} \sum_{k=1}^{N} (\hat{y}_k - y_k)^2, \quad k = 1, 2, \ldots N \quad (14)$$

where $\{y_k\}_{k=1}^{N}$ are samples from the $Y$-axis position signal. The $Y$-axis displacement (or modulation) signal is then obtained as

$$\Delta y(t) = \hat{y}(t) - y(t) \quad (15)$$

The displacement signal $\Delta y(t)$ represents the translational vibrations in the feed direction and is equivalent to the real-valued phase modulation signal in (12). It contains the process-related frequencies which are subject to further analysis. Due to possible imperfections in the setup and other non-modelled process behavior, unwanted linear or nonlinear global trends can sometimes remain in $\Delta y(t)$. By estimating the amplitude offset $m$ and time offset $\tau$, such trends will less likely appear and the acquired signals from different machining tests can be synchronized to a relatively high accuracy to allow comparison between the results from different machining tests. For this work, the usefulness of the recovered modulation signals $\Delta x(t)$ and $\Delta y(t)$ for process monitoring is investigated based on mainly frequency domain analysis.

2.5 Single-revolution signal analysis

Once that the three different cutting stages are identified, the modulation signal in (15) recovered from stage 2 of the cut is examined for monitoring purpose. Specifically, the signal from the single workpiece revolutions is used in the analysis. Given that no additional grooves exist on the workpiece end face, the face turning process becomes a continuous process, from start to finish. No specific tooth-passing frequency, therefore, exists. Furthermore, in the case of a constant cutting speed, when travelling in the radial direction from the larger to the smaller diameter, the period of each workpiece revolution will decrease with time. Thus, to allow a detailed assessment of the progression of the face turning process over time, the encoder signals are segmented based on timing of the workpiece revolutions. This requires the use of the off-line signal synchronization method described in the previous subsection. The time of each workpiece revolution therefore becomes important. In the case of constant cutting speed, the period of the $k$th workpiece revolution will decrease linearly with time as

$$T_k = \frac{\pi}{10^5 v_c} \left( D_0 + (1 - 2k)f \right), \quad (16)$$

$$k = 1, 2, \ldots, N, \quad N = \left\lfloor \frac{D_0 - D_1}{2f} \right\rfloor$$

where $N$ is the total number of workpiece revolutions from the start to the finish of the cut. This implies that the number of samples $f_s T_k$ collected during each revolution will also decrease in a linear manner. Therefore, finding good signal features which are independent of the number of input signal samples may become a major factor to achieve a reliable process monitoring.
3 Experimental setup

The face turning tests were conducted in a 5-axis multitask machine (DMU 160 FD) at Production Technology Centre (PTC), University West, in Trollhättan, Sweden. The workpiece was a solid cylindrical mild steel bar which was machined from an initial diameter of about 306 mm to a final diameter of 60 mm. The actual cutting speed was set to 40 m/min and the feed per revolution was set to 0.3 mm. This gives a gradual increase of the rotational speed from about 42 min$^{-1}$ to 212 min$^{-1}$ over a time span of about 5.9 minutes and a spiral cutting length of about 236 meters. General-purpose turning inserts (WNMG060404-M3 TP200) were used in all cutting tests. The load conditions were altered by changing the depth of cut $d_z$ in the vertical direction according to Table 1. Note that the first test was performed as an air-cut intended to serve as a reference case among the different cuts. Identical straight-line tool paths along the Y-axis, from the outer to the inner diameter towards the center of rotation, were used in all cutting tests.

### Table 1: Cutting data used in the face turning tests.

<table>
<thead>
<tr>
<th>Test</th>
<th>$v_c$ [m/min]</th>
<th>$f$ [mm/rev]</th>
<th>$d_z$ [mm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>40</td>
<td>0.3</td>
<td>0.0</td>
</tr>
<tr>
<td>2</td>
<td>40</td>
<td>0.3</td>
<td>1.0</td>
</tr>
<tr>
<td>3</td>
<td>40</td>
<td>0.3</td>
<td>2.0</td>
</tr>
<tr>
<td>4</td>
<td>40</td>
<td>0.3</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Figure 3: Workpiece clamped onto the work table.

During each cut, the sinusoidal signals from the linear encoders in the feed directions X, Y and Z were acquired using a specially built signal acquisition system compatible with the machine tool’s 1Vpp encoder signal interface. The incremental optical linear encoders (Heidenhain LC 481) feature a resolution $M_L = 50$ sinusoidal cycles per millimeter movement. According to (8), with the actual cutting speed, feed and diameter values, this particular machining process is performed within the carrier frequency interval 10.39–53.05 Hz. A sampling rate $f_s = 15$ kHz was used in all tests. All signal analysis was carried out off-line. The machining process variables based on (1)–(4) and (8) are plotted in Fig. 4. Note especially the non-linear time evolution of the carrier frequency $f_c(t)$ due to the accelerated motion in the feed direction. The cutting speed $v_c$ however, will remain constant throughout the cut.

The images of the cutting tool inserts after each cut are shown in Fig. 5. As can be seen, severe chipping of the cutting edge occurred in the fourth cutting test (3 mm cut) due to a mechanical overload.

4 Results and discussion

The frequency domain analysis is presented for the complex-valued encoder signal and the extracted vibration signatures.

4.1 Frequency content in the complex encoder signal $z(t)$

Ideal Y-feed axis signals $u_A(t)$ and $u_B(t)$ are shown in the left chart of Fig. 6 during 0.6 seconds of the total 5.9 minutes of signal samples. Note that the carrier frequency increases with increasing feed rate during the cut according to the nominal process variables found in Fig. 4. These ideal signals represent the encoder signals in the case when the servo drive is not subjected to any disturbances or vibrations induced by any machining process. These ideal signals only contain a carrier component and are therefore not frequency modulated. The two encoder signals are combined into a complex-valued signal $z(t)$ as defined in (6). Then, by applying the FT to the complex-valued signal $z(t)$ based on the data from the entire cut, the amplitude spectrum of $z(t)$ is obtained as shown in Fig. 6. As also described in Section 2, the amplitudes of the negative frequencies in $u_A(t)$ and $u_B(t)$ will cancel each other, while doubling the amplitudes at the positive frequencies. The decaying trend seen in the amplitude spectrum is due to the continuously decreasing period of the turn table.
A similar spectral analysis was applied to the signals from the different cutting tests as shown in Fig. 7. Note that when additional frequencies are introduced into the encoder signals from the process vibrations and possibly also from the machine tool controller actions as a consequence of the process disturbances, the instantaneous carrier frequency in the encoder signals will be modulated which will generate distorted encoder signals. The signal distortions are relatively small, sometimes hardly distinguishable in the time domain, but often become clearly visible in the frequency domain. Also note in the amplitude spectra that the signal energy is now also distributed over the negative frequencies which implies that, as soon as the modulation from the process vibrations sets in, the signals will deviate from the ideal signal found in Fig. 6.

Although the vibrations signatures are qualitatively apparent in the amplitude spectrum, the amplitude spectrum was converted into a cumulative power spectrum to reflect the collective influence of the vibrations quantitatively. The cumulative power spectra, obtained as the normalized cumulated sum of the squared amplitudes from 0–7500 Hz, were calculated for the different cutting tests using Parseval’s power formula in Fig. 8. The energy in the negative frequency band was first added to the corresponding positive frequencies before the summation of the signal power, to ensure that the total energy was preserved.
Figure 7: Y-axis encoder signals for different conditions of the face turning process after 50 workpiece revolutions (left panel) and the corresponding amplitude spectra (right panel) based on the entire history of the complex-valued signal.

Table 2: Power measurements from Y-axis signals.

<table>
<thead>
<tr>
<th>Test</th>
<th>$P_{tot}$ [V$^2$]</th>
<th>$P_{10.39 &lt; f &lt; 53.05}$</th>
<th>$P_{f &lt; 10.39}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal</td>
<td>0.125</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>1</td>
<td>0.132</td>
<td>99.5%</td>
<td>0.37%</td>
</tr>
<tr>
<td>2</td>
<td>0.132</td>
<td>99.3%</td>
<td>0.50%</td>
</tr>
<tr>
<td>3</td>
<td>0.132</td>
<td>94.1%</td>
<td>3.71%</td>
</tr>
<tr>
<td>4</td>
<td>0.131</td>
<td>90.8%</td>
<td>5.76%</td>
</tr>
</tbody>
</table>

for the different cutting conditions, see Table 2. For the air cut in Test 1, nearly all power can be found within 10–53 Hz and almost perfectly matches the ideal case with zero modulation as the cumulative power reaches almost 100% at 53 Hz.

From the normalized cumulative power spectra in Fig. 8, it can be noted that, as the machine load increases due to the increased vertical depth of cut, the power at the lower frequencies ($<10$ Hz), which are related to the machine tool’s structural components, increases. On the other hand, the spectral power in the carrier band 10–53 Hz decreases with increasing cutting load. The detailed values of these power shifts within different frequency bands are tabulated in Table 2. Interesting to note is that, despite the increasing cutting load, the total signal power over the time span of the cut, will remain almost constant, which implies that the signal power is only redistributed over different frequencies. The nominal signal amplitude of the measured signals was found to be just over 0.5 V
which explains the larger total power value 0.131 $V^2$ when compared with the ideal power of 0.125 $V^2$.

In the most severe cutting load condition in Test 4, which ultimately lead to a severe chipping of the cutting edge, see Fig. 5c, a near 9% total power drop was observed within the frequency band 10.39–53.05 Hz. An increasing trend can be seen in the lower frequency interval 0–10.39 Hz in Fig. 8. The corresponding tabulated power values are found in the fourth column in Table 2, which suggests that nearly half of the total power drop can be found in the frequencies below the lower bound of the carrier band. The remaining power can be found beyond the upper bound of the carrier band up to the Nyquist frequency 7500 Hz. Larger fluctuations in the cumulative power within approximately 2–6 Hz could be observed in Test 4, which suggests a stronger excitation of some of the structural components. This excitation could originate from the increasing rotational frequency from 0.69 Hz to 3.54 Hz which interestingly, for some reason, appears as doubled frequency in the encoder signals. This phenomenon is not within the scope of this paper and therefore not detailed any further.

Even though the results in Fig. 7–8 clearly demonstrate the detectability of machining conditions using encoder signals, the amount of data needed is too large for real-time detection. Hence, accumulating, in this case, 5.9 minutes of data, to obtain e.g. the cumulative power spectrum, is not suitable for on-line process monitoring. In order to reduce the data requirement, processing time and monitoring delays, the vibration signature $\Delta y(t)$ based on (15) will eventually be more useful.

### 4.2 Frequency content in the vibration signature $\Delta y(t)$

The separation of the modulation signal from the modulated carrier is performed using Eq. (5–15) since most conventional demodulation methods either assume a constant carrier and can therefore not cope with time-varying carrier signals, or require too much computational time and for this reason not suitable for real-time usage. Also, in machining, the modulation and carrier frequencies will often be mixed which is why use of bandpass filters to separate these two signal components will most likely fail. To the authors’ best knowledge, the ultimate demodulation method, suitable for real-time demodulation of encoder signals, without the need of making any preassumptions on the nominal tool path geometry nor instantaneous nominal feed speeds, is therefore yet to be discovered. Anyhow, by using the proposed demodulation method, the Y-axis vibration signal $\Delta y(t)$ can be properly recovered from the modulated encoder signals as shown in Fig. 9.

The phase-demodulated Y-axis encoder signals, also known as baseband signals, from start to finish of the cuts, were then subjected to a Fourier analysis. The resulting amplitude spectra from the different cutting tests are also shown Fig. 9. Note that time is converted to an angle $0 \leq \phi \leq 2\pi$ spanned during the workpiece period given by (16) which resulted in an almost stationary view of the on-going process modulations over subsequent workpiece revolutions. It can be seen that a considerable amount of energy still remains in the carrier band 10–53 Hz after the removal of the carrier phase $\theta(t)$. Note that in the ideal case the modulation component is zero and therefore not shown.

These remaining frequency components were originally riding on the carrier wave, representing the process-induced vibrations. The amplitude spectra clearly indicate that the studied face turning processes exhibit quasi-stationary dynamics. This is mainly due the simultaneous rotational and translational accelerations of the work table along the Y-axis in combination with an on-going degradation of the cutting tool. A dominant peak can be found at 28 Hz which is more energized with increased cutting load, especially in Test 4 when the tool chipping occurred, resulting in an significant amplitude jump near 28 Hz.

The recovered vibration signature $\Delta y(t)$ resembles noise because of its small amplitude. For the air cut (Test 1), this “noise”-like vibration is similar to a white noise with a relatively flat amplitude spectrum for the frequency band 10–53 Hz. However, this vibration “noise” becomes colored by the cutting process, exhibiting different vibration modes for different machining conditions. As a result, it is confirmed, that the internal encoder signals can be used to detect various machining conditions.

An interesting observation from the cutting tests was that in the air cut (Test 1) and the 1 mm vertical depth of cut (Test 2) the extracted $\Delta y(t)$ signal was mainly composed by a low frequency (LF) component together with a riding high-frequency (HF) component as seen in Fig. 9. However, in cutting Test 3 and 4, corresponding to the 2 mm and 3 mm vertical depths of cuts respectively, the LF-components in $\Delta y(t)$ were almost drowned in the 28 Hz vibration mode in terms of energy, which tend to increase significantly. Separating the individual frequency components in order to conduct a more detailed analysis would require additional filtering or the use of more advanced signal processing methods, such as Singular Spectrum Analysis (SSA), which was never attempted for this paper.
Similar spectral analysis was also carried out for the X- and Z-axis vibration signals which is presented in the following subsection.

4.3 Vibration signatures from the X- and Z-axis

In the two orthogonal feed directions X and Z the phase functions of the encoder signals resemble ordinary vibration signatures and do not contain any real carrier phase. The power distribution is almost uniform over the negative and positive frequencies. Thus, it is not necessary to perform the phase demodulation as given in (11). In this case, by setting $\theta_c(t) = 0$ the modulation signal can be obtained directly by (7) and converted into their physical units by the scaling in (12). Since the previously presented global power spectra are unable to reveal the changing process conditions between the different tests to any significant detail, other than notable energy shifts, a local analysis based on a windowed FT applied to the modulation signals, was therefore undertaken.

As can be observed in Fig. 9, the frequency band 20–30 Hz tend to be excited more than the other frequencies. A window-based analysis using a window length of 1 second, was therefore conducted where the maximum absolute amplitudes of the 20–30 Hz components were extracted from all feed axes within each time window as shown Fig. 10. Except for the brief seconds in the beginning and end of the tests, the entire machining conditions were essentially quasi-static as indicated by the Test 2 data. In Test 3 the Y-axis amplitude increased only slightly towards the end. However, in Test 4 the process became far from quasi-static. Note that after about 5 minutes of cutting, during Test 4 the maximum displacement amplitudes of all three axes in Test 4 apparently decline which
indicate significant changes in the machining conditions despite of the fact that the feed per revolution remains the same. This change could be related to chipping of the cutting edge seen in Fig. 5c. Therefore, although it is apparent that the amplitudes increase with higher feed per revolution, this also implies that the use of the Y-axis modulation alone may lead to an incorrect interpretation of the actual machining process condition.

The common belief is that tool chipping should reveal itself easily in any signals related to cutting force. However, this is not always true. As shown in the vibrational time signal of Fig. 9 from the encoder, it is not clear how the amplitude of $\Delta y$ is changed due to tool chipping because the amplitude is changing constantly from the ongoing modulations. Even in Fig. 10, when the maximal amplitudes of $\Delta y$ were recorded over time, when a large amplitude increase of Test 4 (red curve, middle chart of Fig. 10) at minute 5 was observed, one could not be sure that it was due to tool chipping because the amplitude soon reduced despite it was under the same cutting condition. From the common belief, one would think that the amplitude spike of $\Delta y$ should stay high but it was not the case. Therefore, a more reliable indicator of the tool wear is needed and we would explore the relationship between flank wear and the ratio of $F_y/F_x$, as discussed in the next section.

4.4 Displacement ratio as tool wear indicator

As suggested by Jeppsson in [5] the ratio between the radial and tangential cutting forces is sensitive to the on-going tool wear process. We explore the combination of the X-axis and Y-axis vibration signatures for tool wear detection, instead of measuring the cutting forces as in [5]. The hypothesis is that the vibrational amplitude along a feed axis in the feed direction would be proportional to the cutting force along that axis. As shown in Fig. 10, if the face turning process is viewed in the perspective of an OCM, the feed axis in the Y-direction corresponds to the radial (or thrust) direction, while the X-axis corresponds to the tangential direction. The flank wear will increase the radial force $F_y$ along the Y-axis, while the tangential cutting force $F_x$ will remain relatively unaffected.

The resulting effect is that the cutting force ratio $F_y/F_x$ will be indicative of tool flank wear. Therefore, as an indirect measure of this cutting force ratio, we introduce the displacement ratio as an equivalent and viable approach to monitoring the on-going tool wear process and for the detection of the occurrence of severe tool chipping which will be discussed next.

4.5 Control chart evaluation of the displacement ratio

The relatively large fluctuations in the displacement ratio in the 20–30 Hz range during the machining process suggest an on-going change in the process dynamics. These variations however, do not represent global trends in the ratio and need to be properly handled by a monitoring system. As a tool wear indicator, the displacement ratio $r(k)$ between the maximum absolute modulation amplitudes in the Y- and X-directions obtained directly from the amplitude spectrum of the modulation signals within the window $k$ as given by

$$r(k) = \frac{\max |\Delta y(\omega)|_k}{\max |\Delta x(\omega)|_k}, \quad \omega = 2\pi [20, 30] \text{ rad} \cdot \text{s}^{-1} \quad (17)$$

where $k$ is the actual window number. The use of Statistical Process Control (SPC) allows a process variable, such as the displacement ratio defined in (17), to be monitored in real-time. In this particular case, using a fixed window...
length of 1 second and a signal decimation rate 15 (i.e. downsampling from 15 kHz to 1 kHz), the X- and Y-axis modulation signals could be represented by 999 samples per window (when using 50% window overlap and after adjustment to an odd number of samples per window). The displacement ratio, based on the maximum absolute displacements within the frequency band 20–30 Hz according to (17), were then evaluated, leaving totally 711 observations of the displacement ratio. The r-values were then averaged over \( n = 10 \) windows to reduce the effect from the fluctuations, which further reduced the data set to 71 observations of the averaged r-values from the start to the finish of the cut.

For a number of collected subgroups (or partitions) with mean values \( \bar{X} \) and standard deviations \( S \) of the displacement ratio (17). The intention is to monitor the evolution of \( X \) by using a statistical process control (SPC) chart. Different SPC charts were evaluated; the conventional Shewhart (or X-bar) chart and the Exponentially Weighted Moving Average (EWMA) charts using fixed lower and upper control limits (LCL and UCL respectively). It was found that these conventional charts require relatively long recordings of \( X \) and \( S \) before reliable control limits could be established, which in practice would give unacceptable delays in the monitoring system. This is due to the initial non-stationary stage of the cut which need several revolutions before a settling into the quasi-stationary cutting stage. Thus, to accommodate such factors, the modified EWMA chart [10] with time-varying control limits was adopted to monitor the averaged displacement ratio. The EWMA statistic \( Q_t \), based on Single Exponential Smoothing (SES), is calculated as the linearly weighted sum of the current and previous observations, as given by

\[
Q_t = \lambda X_t + (1 - \lambda) Q_{t-1}, \quad t = 1, 2, 3, \ldots \tag{18}
\]

where \( 0 < \lambda \leq 1 \) is the actual smoothing constant (also known as the forgetting factor) which allows to take into account also previous observations of the control variable \( X \). The lower and upper control limits for the EWMA chart up to subgroup with time index \( t \) are then continuously updated and determined as [11]

\[
\begin{align*}
\text{LCL}_t &= \bar{X}_{t-1} - c \frac{S_{t-1}}{\sqrt{(1-\lambda)^n}} \\
\text{UCL}_t &= \bar{X}_{t-1} + c \frac{S_{t-1}}{\sqrt{(1-\lambda)^n}}
\end{align*}
\tag{19}
\]

where \( n \) denotes the actual subgroup size (or internal window length) used by the EWMA chart, \( \bar{X}_t \) is the calculated mean of the process variable \( X \) and \( S_t \) is the mean standard deviation of \( X \) up to the subgroup \( t \). As with any other moving average based metric, the response from the EWMA will be delayed. In this case, the initial delay corresponds to \( n = 10 \) subgroups. The initial value \( Q_0 \) is based on the first \( n \) inputs and is not a fixed value.

It can be noted that by using \( \lambda = 1 \) the EWMA chart translates to the conventional X-bar chart with variable control limits which makes the EWMA chart relatively flexible. The control constant \( c \) in (19) determines the width of the EWMA control corridor. In this work, the values \( \lambda = 0.5 \) and \( c = 10 \) were found to be suitable based on data from Test 2. These parameter values were also used without changes when analyzing the data from Test 3 and Test 4.

The EWMA statistic \( Q_t \) for the cutting tests 2-4 are shown in Fig. 12. An abnormal process condition, due to severe tool degradation, can be triggered whenever \( Q_t < \text{LCL}_t \) or \( Q_t > \text{UCL}_t \). In this particular case, we found that using time-varying control limits makes the control scheme more reliable since it becomes more insensitive to random fluctuations in the control variable \( X \) which can be expected during in-process monitoring. The control chart will eventually also show an improved adaptation to different machining conditions when compared with fixed control limits and therefore expected to become more responsive to changing process condition since the responsiveness of the chart is largely controlled by the \( \lambda \)-value. More sophisticated EWMA charts which primarily make use of an adaptive \( \lambda \)-value can be found in e.g. [9, 10].

### 4.6 In-process tool wear monitoring

Based on equations (18) and (19), tool wear control charts for the displacement ratio defined in (17) were constructed for the three machining tests over the entire data sets of Fig. 10. From the resulting EWMA charts found in Fig. 12, it can first be noted that the process conditions are clearly different between the 1 mm, 2 mm and 3 mm cuts where the last two are considered as roughing operations and most likely to be monitored due to the higher tool wear rates. In both Test 2 and Test 3, the \( Q_t \)-values stay within the control limits, while the 1 mm cut is more like finishing cutting. The larger fluctuations seen in the 1 mm cut are due to the relatively low \( \Delta x \) values, which contribute to lower signal-to-noise ratios, which explains the wider control limits in this case. For the 3 mm cut used in Test 4, a significant change in the process condition due to the gradual tool breakdown can be noted in the third EWMA chart where the EWMA statistic exceeds and remains above the UCL after approximately 5 minutes into the cut.

One more consequence can be derived from Fig. 12. A linear regression line can be defined over the ratio data for
each control chart. The slope of this line could represent the tool wear rate. The calculated “EWMA tool wear rate” for the 1 mm cut is 0.17 min$^{-1}$ for the 1 mm cut, 0.24 min$^{-1}$ for the 2 mm cut. For the 3 mm cut, a tool wear rate between 1.5–4.9 minutes is found to be 0.26 min$^{-1}$. However, a drastically different rate 1.56 min$^{-1}$ (a near 600% increase) can be observed from 4.8 minutes into the cut until the end of the cut. Based on the tool wear images of Fig. 5c, the tool was obviously chipped at the flank surface at some point during the 3 mm test. Based on the calculated tool wear rate, the chipping most likely occurred around 4.8 minutes into the cut, resulting in a jump in the wear rate. Finally, the advantage of using the ratio defined in (17) as pioneered by Jeppsson at Boeing, is obvious if we compare the raw signals in Fig. 10 and the EWMA charts in Fig. 12. The results in Fig. 12 are consistent with the tool insert conditions found in Fig. 5a-c. The tool wear to the cutting edges and flank surfaces in Test 1 and 2 are negligible, with only some discoloring of the flank surfaces, which is consistent with the linear slopes in the dynamic EWMA chart.

A likely explanation for the amplitude change is that when the tool wear is small, the feed per revolution (depth of cut) is essentially the same, but the cutting became less efficient, resulting in higher cutting forces and higher displacement amplitudes. However, when the tool had chipped, the cutting edge would recede causing a reduction in the depth of cut coupled with lower cutting efficiency, see Fig. 11. If the reduction of the depth of cuts outweigh the cutting efficiency, the cutting force could reduce. Judging the severe chipping found in Fig. 5c the most likely explanation for the decreasing displacement magnitude starting at around 5 minutes into the cut is due tool chipping.

The in-process tool wear detection scheme of Fig. 12 can be implemented for use in real-time monitoring. The encoder signals from the X- and Y-axis could be sampled continuously to calculate the EWMA charts to assist the operator in tool insert change decisions. Finally, the use of the internal encoder signals is a viable alternative to the conventional use of additional sensors in process condition monitoring.

5 Conclusion

This paper has investigated the use of internal position encoder signals to monitor a special face turning process with constant feed per revolution and machining speed. The load conditions were altered by using various vertical depths of cuts.

A signal processing method by converting encoder signals into a complex-valued form for amplitude spectrum analysis was presented (Eq. 5–6). A new vibration signature extraction method based on the phase functions was then developed (Eq. 7–12). Based on these two methods, the encoder signals could be analyzed in the frequency domain.

It was found that various machining conditions could be reflected by the amplitude spectrum of the encoder signals along the direction of the feed axis (Fig. 4–5). The cumulative spectrum was then used to provide quantitative changes in the amplitude spectrum. The cumulative spectrum in Fig. 8 indicated that the spectral energy would
shift from the frequency band above 10.39 Hz towards the ones below. This shift in the spectral energy became larger at higher cutting load which manifests itself as distortions in the encoder signals (Table 2). The embedded vibration signatures extracted from the encoder signals provided additional detectability of the machining condition with distinguishable spectral modes. In particular, tool chipping manifested itself as significant amplitude changes at a specific frequency band 20–30 Hz in the extracted vibration signatures. However, the displacement magnitude along the feed axis was not shown to be a reliable indicator of the tool condition. The detailed analysis of the displacement ratio (17) based on the XY-plane modulations was proven to be a robust tool wear indicator. More specifically, in Test 4, when tool chipping occurred, this could be detected using the EWMA SPC chart as shown in Fig. 12. The EWMA control charts also could help in calculating and establishing an average tool wear rate. When this this tool wear rate value jumped in combination with breach of the control limits could provide a highly robust condition monitoring scheme. However, new experiments are required to confirm the tool wear rate estimation.

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References