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WAVELET DECOMPOSITION OF CLOSE-TO-PROCESS ACCELERATION SIGNALS FOR WEAR MONITORING

Highly automated and unmanned manufacturing requires process monitoring and in-process control to prevent damage to the workpiece or machine tool due to tool failure. The positioning of sensors close to the process is crucial to the success of such monitoring. One way of achieving this in machining applications is to equip toolholders with sensor systems. The Institute of Production Engineering and Photonic Technologies (IFT) has developed a sensory tool holder based on MEMS acceleration sensors that measures radial vibrations. The sensory tool holder system can be used to monitor production processes such as milling, drilling or tapping. In order to effectively use the signals from the sensory tool holder system for closed-loop control, it is necessary to convert these signals into characteristic values. This paper shows that wavelet decomposition of process-related acceleration signals is suitable for generating such a characteristic value for wear monitoring of end mills. Long-term roughing and finishing data from a real production process were analysed for this purpose.

1. INTRODUCTION

The machining of complex parts, unpredictable part defects and spontaneously increasing tool wear create difficult conditions for the implementation of automated manufacturing. This is often combined with high tooling costs and high financial risks in case of failure. Sensors in tooling systems are a suitable means of monitoring, supervising and controlling machining operations. Tooling systems with sensing capabilities are being developed to provide a reliable and fast method of gaining deep insight into the machining process [1]. This provides real-time information about the ongoing process or enables automatic stops and adjustments to the machining operation.

Tool condition monitoring is typically based on sensory characteristic features extracted using signal processing techniques such as statistics, Fourier and wavelet transform [2]. Wavelet transform and decomposition for feature extraction has been used in a wide range of

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condition monitoring applications [3]. In machining applications, in addition to tool condition monitoring [5], it has been successfully used to monitor machining stability [4].

Fang et al. [6] used Daubechies wavelets (Db8) to analyse cutting vibration signals in turning of Inconel 718 and showed that the average energy of the wavelet coefficients can be used to evaluate tool edge wear. Feature extraction and pattern recognition of chip shape typology was achieved by [7] using wavelet decomposition of a force signal from turning of AISI 1045 carbon steel. In [8], Daubechies wavelets (Db3) were used to decompose cutting force signals collected during milling of titanium alloy Ti-6Al-4V at variable cutting speeds from 80 to 360 m/min. The use of a wavelet coefficient is presented to be suitable for monitoring cutting stability and tool wear. In [9], tool condition is monitored using vibration and acoustic emission signals during high-speed milling of Ti-6Al-4V. The results show that wavelets and machine learning algorithms can be used to classify tool conditions. However, all of these studies were carried out using stationary measuring tools. Bending moment signals from a multi-sensor tool holder were used by Schuster et al. [10] to detect machining instabilities during milling. Reliable chatter detection was achieved by analysing the mean signal energy corresponding to the high frequency coefficients of a discrete wavelet transform. Xie et al. [11] used a standard tool holder equipped with an acceleration sensor and Haar wavelets to decompose the measured vibration signal in 3 levels. It was stated that the energies of different frequency bands from the wavelet decomposition were suitable as features for tool condition monitoring.

In this paper, wavelet decomposition was done to analyse acceleration measurement data from the face milling of a screw support surface on a connecting rod in a series production process. A sensor-integrated tool holder developed by Bleicher et al. [12] was used to automatically collect these close-to-process data. The collected data are analysed in a post-process analysis. It can be revealed that wavelet decomposition is suitable for generating characteristic values to determine the tool wear condition of end mills in a series production process.

2. MATERIALS WAVELET ANALYSIS

Wavelet transform is a mathematical technique for analysing time series signals or images. It decomposes the signal into detail components and scale components at different scales. The detail components are accommodated in the wavelet coefficients. The scale component can be interpreted as a smooth version of the signal at the different scales. The decomposition can be performed using any family of wavelet functions. There are many types of wavelets - Haar wavelets, Daubechies wavelets, Coiflets wavelets and more. For a detailed description of wavelet transform see [13, 14].

The classical discrete wavelet transform (DWT) requires that the length of the signal be expressed as $N = 2^k$ for $k \in \{1,2,3,...\}$. In contrast to the DWT, the maximum overlap discrete wavelet transform (MODWT) can be applied to the signal of any length N. Both types of wavelet transform, DWT and MODWT, are energy preserving [13]:

$$\|X\|^2 = \sum_{j=1}^{J_0} \left\|\widetilde{W_j}\right\|^2 + \left\|\widetilde{V_{J_0}}\right\|^2 \tag{1}$$

where $\|X\|^2 = \sum_{i=0}^{N-1} X_i{}^2$ is the energy of the signal, $\widetilde{W_j}$ are wavelet coefficients at level j and $\widetilde{V_{J_0}}$ is the scale coefficient at level J_0. Based on this equation the sample variance of the signal σ_X^2 can be decomposed [13]:

$$\sigma_X^2 = \frac{1}{N}\sum_{j=1}^{J_0}\left\|\widetilde{W_j}\right\|^2 + \frac{1}{N}\left\|\widetilde{V_{J_0}}\right\|^2 - \bar{X}^2 \tag{2}$$

with $\bar{X}$ as a sample mean. Define

$$\omega_j = \frac{1}{N}\left\|\widetilde{W_j}\right\|^2 \tag{3}$$

for $j = 1,\dots,J_0$ as an indicator of the variance of the wavelet coefficients at level j. This measure shows a contribution of the variance at level j to the variance of the signal. Niaki et al. [15] show that, among other features, the variance of the wavelet coefficients is a possible characteristic of tool wear.

From a practical point of view, the inputs to the wavelet transform are the signal, the wavelet function and the maximum decomposition level J_0. The computation of the MODWT is done using the R package wavelets [16]. In general, the optimal choice of wavelet function and maximum decomposition level are difficult to find. Fugal [17] notes that a trial-and-error method is usually useful to find the best mother wavelet. Teti et al. [18] also state that different researchers have chosen different wavelets and decomposition levels in the past, but there is no clear explanation as to why the particular wavelet was selected. Niaki et al. [15] show that the Daubechies3 (Db3) and Daubechies4 (Db4) wavelet decompositions produce characteristic values that correlate with tool wear.

3. EXPERIMENTAL SETUP

For the investigations, a 4-axis CNC milling centre (Makino a61nx) for connecting rod manufacturing was equipped with the ICOtronic system [19]. A schematic design of the sensory toolholders in use is shown in Fig. 1. It is an HSK-A63 toolholder with a 20 mm diameter hydraulic chuck developed by Bleicher et al. [12] and is equipped with a ± 50 g MEMS acceleration sensor for measuring radial acceleration positioned in the axis of rotation. The measured radial acceleration is sampled at 9.6 kHz and can be continuously streamed for 8 h. The digitised signal is sent via Bluetooth Low Energy to a transceiver unit located in the machining area.

For automatic data acquisition of the sensor integrated tool holder a signal processing unit was connected with the FOCAS interface of the machine's FANUC control via Ethernet. When the sensor-integrated tool holder was changed into the workspace of the machine tool, the automatic start of data acquisition was initiated by the exchange of macro variables between the CNC of the machine tool and the signal processing unit. Two processes were investigated - roughing and finishing of the screw support surface of a connecting rod. Therefore, the machining centre was equipped with a total of four sensor integrated tool holders. This meant that two tools were available for each process and ensured that the production process could be monitored continuously, without interruptions caused by the need to recharge the battery of the sensory tool holder. When the end of tool life was reached, the tool holder with the clamped tool is removed from the machine´s tool magazine so that a new tool could be inserted in the company's tool preparation department. After recharging, the toolholder is returned to the machine once the sister tool has reached the end of tool life.

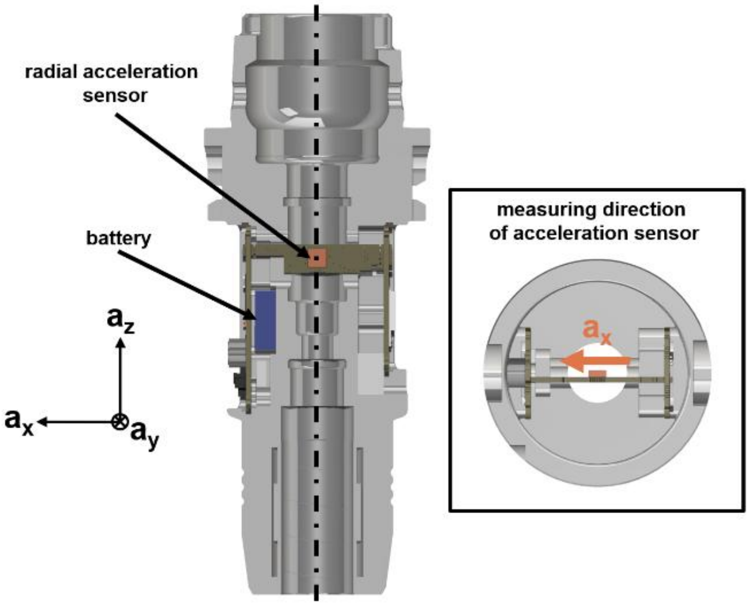

Fig. 1. Sensor integrated toolholder

The connecting rod material is Ti-6Al-4V. The end mill SECO JS754160E2R200.0Z4-HXT with a diameter of d = 16 mm and four cutting edges was used for roughing and the end mill SECO RM-JS720160R195-HXT again with a diameter of d = 16 mm and six cutting edges was used for finishing. During the measurement period, tooling tests were carried out using in-house manufactured tools for both roughing and finishing. These tools had the same diameter and number of cutting edges, but showed differences in the rounding of the cutting edges. The material allowance for the finishing operation is 0.15 mm. The machining parameters for the two process steps and the optimised parameters for finishing are given in Table 1.

Twelve connecting rods are clamped in one set-up. For each connecting rod, two screw-support surfaces have to be machined. Thus, the acceleration signal, measured by the sensor integrated tool holder, includes the machining of 24 surfaces. Figure 2 shows the clamping situation of the twelve con rods and the tool path for machining the screw support surface.

Table 1. Machining parameters

process	Cutting speed m/min	spindle speed 1/min	feed rate mm/min	cutting depth a_p mm
roughing	40.2	800	308	2
finishing	78.4	1560	168 / 336	0.15
finishing optimisation 1	78.4	1560	168 / 336	0.15
finishing optimisation 2	78.4	1560	336	0.15

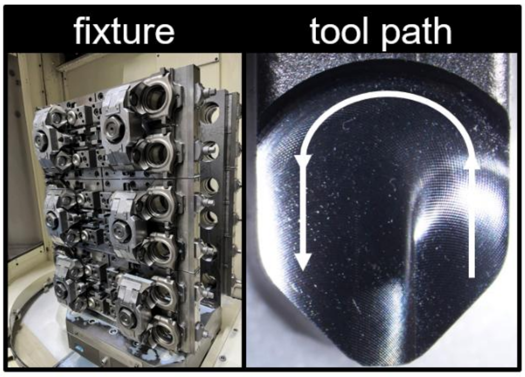

Fig. 2. Fixture and toolpath

4. SIGNAL ANALYSIS AND RESULTS

Seven levels of Db4 wavelet decomposition were applied to the roughing and finishing acceleration data. Due to the continuous process monitoring, measurements of both, the new and the worn tool are available and a signal comparison between these two tool states is possible. The original signal and the first three wavelet coefficients of the decomposition are shown in Fig. 3 for roughing and Fig. 4 for finishing. The vibration signal from machining 24 screw support surfaces with the new tool is shown in red and that of the worn tool is depicted in black. By visually comparing the original signal and the wavelet decomposition coefficients, it is possible, to evaluate which coefficient could be relevant for assessing tool wear. The roughing process presented in Fig. 3, demonstrates that the amplitudes of the wavelet coefficient at level one for the worn tool are significantly higher than the original signal.

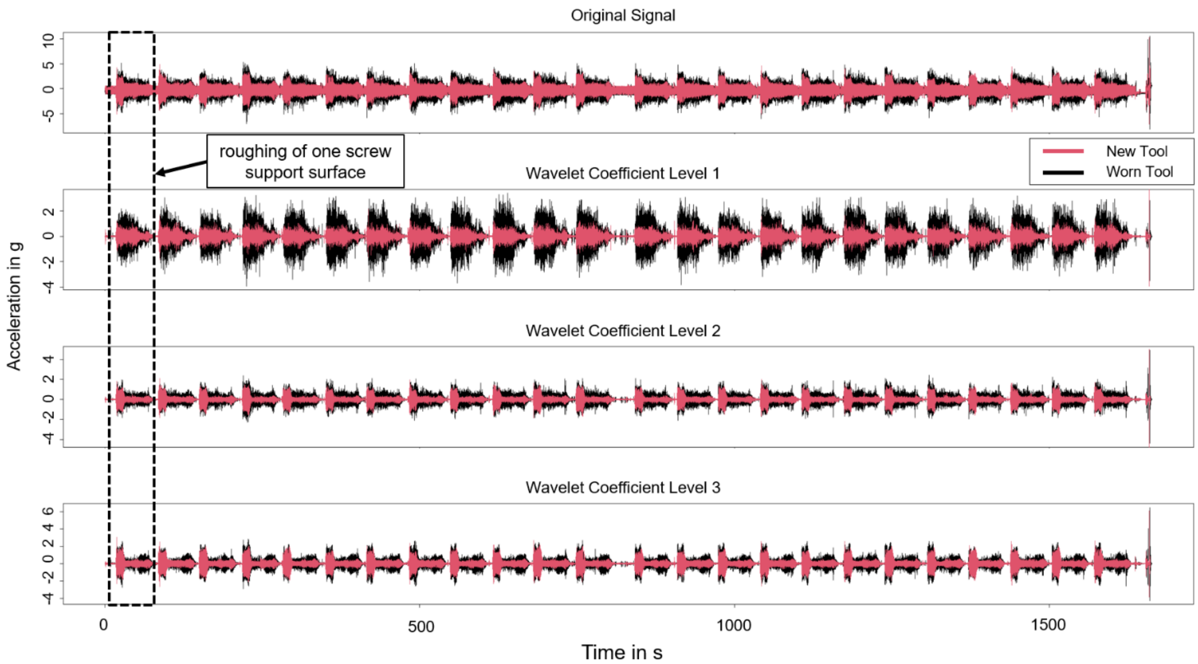

Fig. 3. Wavelet decomposition of acceleration signal of roughing process

For the finishing process, wavelet coefficients at level two and three show the largest differences in amplitude between the new and the worn tool, as it is presented in Fig. 4. These assessments of the time series of the wavelet decomposition show that such a signal decomposition facilitates an optical signal analysis to determine their wear condition.

In the next step, the variance ω_j of the wavelet coefficients (shown in Figs. 3 and 4) was calculated using Equation (3). This approach condenses the differences in wavelet coefficient amplitudes into a single characteristic value. For the long-term analysis, the calculation was applied to the complete machining dataset. As outlined earlier, the first decomposition level ω_1 serves as a reliable indicator of tool wear in the roughing process, while the third decomposition level ω_3 provides a measure of wear in the finishing process. By plotting these variances as time series, the progression of tool wear over time can be systematically monitored. This means that each machining setup - corresponding to the production of 24 screw support surfaces – is represented by one characteristic value, which corresponds to the wear state of the tool at that point in time.

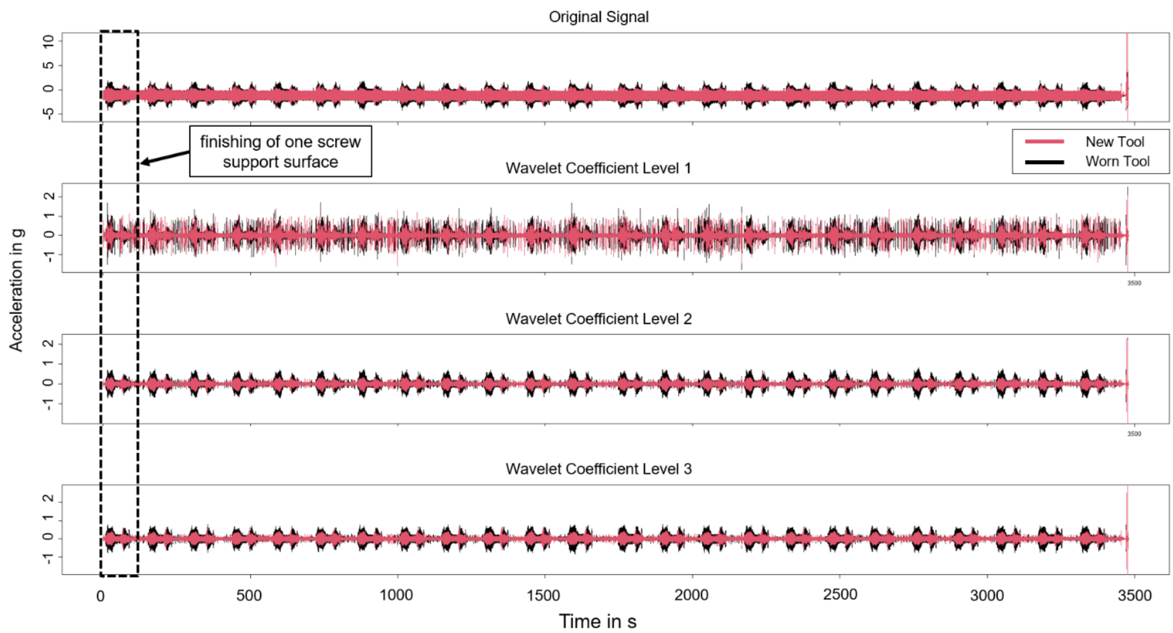

Fig. 4. Wavelet decomposition of acceleration signal of finishing process

Fig. 5 shows the variance ω_1 for the roughing process. Each data point corresponds to one machining setup, with colour coding used to distinguish between the two replacement tools (green and blue). A clear correlation between ω_1 and tool runtime is visible: as tool wear increases, so does the variance. This consistent trend demonstrates that ω_1 is a possible indicator of tool wear in the roughing process. Moreover, the stability of this parameter over the extended observation period confirms its deterministic nature, supporting the feasibility of automated wear detection based on defined threshold values.

Notable fluctuations in ω_1 are also observed. These variations are attributable to several factors, including tests with in-house manufactured tools, tool life experiments, and coolant renewal. The in-house tools exhibited lower vibration amplitudes at the onset of use but, owing to their extended nominal tool life (100 minutes compared with 50 minutes for the original tools), they demonstrated considerably higher vibration levels at the end of their service life. For the original tools, when the tool life threshold was artificially extended to 100 minutes, higher variance values were similarly observed, as evident in the June test campaign. Additionally, a marked increase in ω_1 was recorded following coolant renewal after the annual plant shutdown in mid-August. This effect is plausibly linked to improved frictional conditions.

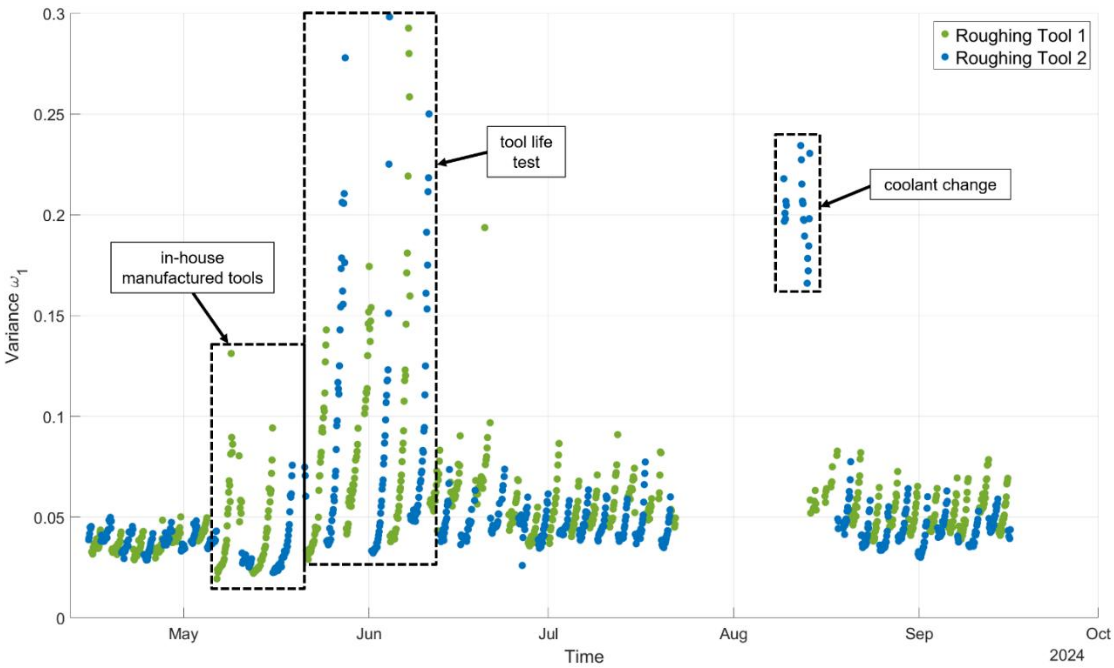

Fig. 5. Variance of wavelet coefficient level 1 for roughing

Fig. 6 depicts the variance ω_3 for the finishing process, with the point colours indicating again the respective replacement tools (black and red). Here again, a clear correlation between variance and tool usage is discernible, enabling the definition of a threshold-based criterion for identifying critical wear states. Tests conducted with in-house manufactured tools over a two-week period in May are also reflected in the data. Although these tools demonstrated improved vibration characteristics overall, the results revealed a higher degree of variance, which may be attributed to limited process repeatability and variability in the in-house grinding process.

Two process optimisations aimed at reducing cycle time were also implemented during the observation period and are clearly reflected in the ω_3 values. These adjustments resulted in a modest increase in variance at the beginning of tool life. Because the nominal tool life setting remained constant, the reduction in machining time - achieved through increased feed rates - allowed a substantially greater number of screw contact surfaces to be machined per tool. In the second optimisation stage, the cycle time was reduced by 43%, enabling each tool to machine an average of 618 screw support surfaces, compared with 432 in the baseline condition. Although the higher feed rates resulted in elevated ω_3 values, the required surface roughness remained within tolerance limits. This outcome indicates that the previously applied tool life limit was conservative.

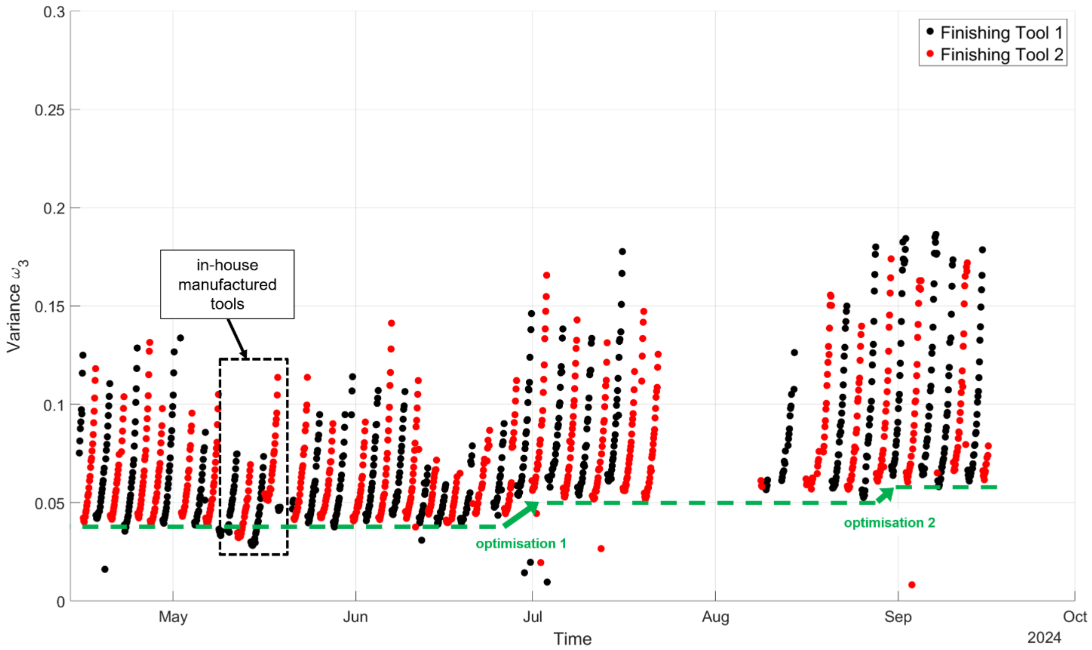

Fig. 6. Variance of wavelet coefficient level 3 for finishing

5. CONCLUSION

Tool wear monitoring is critical in modern manufacturing processes as it can simultaneously reduce machine downtime and increase productivity. This paper shows that it is possible to perform in-line process monitoring using close-to-process data. Wavelet decomposition using a Daubechies Db4 wavelet can be used to generate characteristic values for roughing and finishing operations that exhibit deterministic behaviour for assessing the state of wear of end mills. This allows wear detection to be implemented in highly automated production using simple threshold rules. It was also demonstrated that changes in the coolant, slight changes in the tool contour (rounding of the cutting edge) and changes in tool runtime are detectable in the data.

In future steps, further types of tools will be investigated together with additional workpiece materials (steel) and additional workpiece features in order to verify the generality of the presented evaluation methodology.

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