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Retrofittable vibration-based monitoring of milling processes using wavelet packet transform

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Abstract

An important aspect of the overall quality of machined parts is surface roughness, which depends on cutting parameters, tool condition, and machine vibrations. Online surface roughness prediction in milling operations can reduce set up time and assist in determining economic cutting parameters. However, the adoption of existing solutions in industrial production is inhibited by lacking integration in an open and retrofittable architecture. In this contribution, a solution for surface roughness estimation by vibration monitoring is developed as part of a retrofitting kit. Wavelet packet transform is used to filter the vibration signal, then the roughness of the generated surface is estimated. The approach is tested in milling experiments.

Keywords: Process Monitoring; Vibration; Machine Tool; Wavelet Transform; Surface Roughness; Milling.

1. Introduction

In the context of mass customisation, a higher level of automation is required when planning and optimising manufacturing processes. An important aspect of the overall quality of machined parts is surface roughness, which depends on cutting parameters, tool condition, and machine vibrations [1]. Ideal parameters with respect to quality, cycle time and costs are difficult to determine, especially due to the dynamically changing nature of machining processes and the variation of vibration properties in individual machine tools [2]. Monitoring of vibration data from the spindle enables an online estimation of surface quality [3,4], thus shortening the feedback loop for quality control and enhancing process planning. Methods used in this context for signal processing, analysis and modelling include fast Fourier transform (FFT) [5], singular spectrum analysis (SSA) [6], response surface methodology (RSM) [7,8] and artificial neural networks (ANN) [3]. Additionally, studies have shown that analysis of vibration signals using wavelets can detect faults and failures in machinery and in milling processes [9–11].

Despite extensive research in the field of process monitoring and individual efforts to implement monitoring solutions in industrial manufacturing, these have not yet enabled a widespread adoption. This challenge is representative of the general situation concerning the adoption of Industry 4.0 approaches in discrete manufacturing: many existing machines are not equipped with the required technology, implementation is mainly confined to isolated stand-alone solutions and pilot applications [12]. Existing solutions rely on complex machine and process models or on the costly integration of force measurements, requiring modifications of the new spindle or reducing the position range of feed axes. In order to benefit from the advantages of monitoring on a larger scale, a modular retrofitting kit was developed, in which several data sources can be combined and used for several monitoring functions [13]. The present contribution concerns an application within this retrofitting kit, using data from an accelerometer to monitor vibration during machining, with the aim of estimating surface roughness and detecting the wear condition of cutting tools. The online time-frequency analysis of vibration signals is based on wavelets.

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2. Theoretical background

This chapter describes the mechanical principles of surface generation and existing work on surface roughness, followed by time-frequency analysis using wavelets.

2.1. Surface generation and vibration

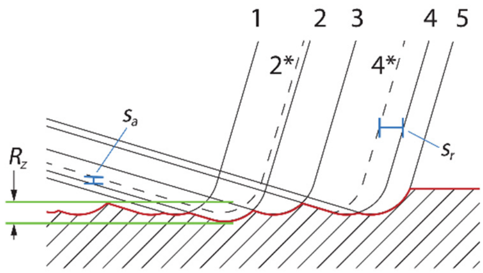

Fig. 1: Surface profile after one revolution

The superposition of feed rate and tool geometry lead to an uneven surface finish in machining processes, even when dynamic forces are neglected [14]. Surface finish in turning can be predicted with static surface roughness models [15].

Baek et al. [16] introduced a surface roughness model for face milling operations, which includes static and dynamic components of the cutting process. The static components account for cutting parameters and insert runout errors due to manufacturing errors of body and insert, which leads to an uneven surface texture as depicted in Fig. 1. Radial runout errors s_r of inserts cause an inconsistent feed per tooth and thus displacement between cutting tool and workpiece due to the impact, which is modelled by the dynamic components. Fig. 1 also shows that axial runout errors s_a influence surface topology, which in turn determines the surface roughness R_z. Furthermore, forced vibration marks lead to a drastic decrease in surface quality.

Marinescu et al. [17] found that surface finish depends in large parts on relative vibration of the cutting tool and workpiece and multiple studies [5,18,7] link tool vibration to surface roughness in turning operations. Chen et al. [6] used singular spectrum analysis to confirm that dominant factors of the vibration amplitude affect surface roughness in milling operations. By using cutting parameters and vibration as inputs to an artificial neural network, Khorasani and Yazdi predicted surface finish with 99% accuracy [3].

In machine tools, vibrations are also caused by auxiliary systems such as coolant pumps and electrical motors, though the largest contributing component to vibrations at the cutting tip are forces generated by the cutting process itself. Tool life, part accuracy and surface finish correlate with these cutting forces, which in turn depend on several factors such as tool geometry, cutting conditions and workpiece material [19,20].

2.2. Time-frequency analysis using wavelets

When analysing signals such as the acceleration due to vibration in machining, it is helpful to consider both their periodic components in the frequency domain and changes over time. A widespread method for performing this time-frequency analysis is the short-time Fourier transform (STFT), consisting of a Fourier transform with a sliding time window. The length of the window determines both the frequency resolution and the time resolution, requiring a trade-off: high frequency and time resolution cannot be achieved at the same time, as shown in Fig. 2 [21].

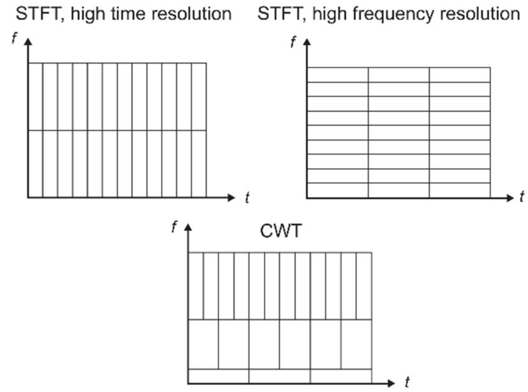

Fig. 2: Time and frequency resolution of STFT and CWT

The introduction of wavelet transforms facilitates time-frequency analysis in many sciences, including engineering. In machining, it has been successfully applied to signals for tool condition monitoring [22]. The continuous wavelet transform (CWT) is defined as:

$$W_{\psi}(s,u) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t)\, \overline{\psi}\left(\frac{t-u}{s}\right) dt \tag{1}$$

where $\overline{\psi}$ denotes the complex conjugate of ψ.

The basis in the CWT consists of wavelets that are constructed by translating a mother wavelet ψ by a shift s and dilating it by a scale u. In contrast to the constant time-frequency resolution of the STFT, resolution of the CWT depends on the frequency of the signal: high time resolution and low frequency resolution at high frequency of the wavelet and vice versa (Fig. 2) [23]. Applying CWT on a signal yields wavelet coefficients, whose physical interpretation indicates the variation of energy of the signal. The scalogram is obtained by squaring the coefficients and can be used for tool condition monitoring and fault detection of a wide variety of machinery [24].

Due to the nature of CWT, results contain overlapping and therefore redundant information [25] and it is computationally slow. Discrete wavelet transform (DWT) attempts to solve both issues by passing the signal through a quadrature mirror filter bank, from which the low-pass approximation (abbreviated "A") and high-pass details (abbreviated "D") are obtained. Depending on the desired level, DWT is applied to the approximation part of the previous level: Fig. 3 shows DWT to the 4th level, also known as multiresolution analysis [26]. DWT solves the aforementioned issues of data redundancy and computation speed, however, high frequency information is disregarded [27]. Wavelet packet transform (WPT)

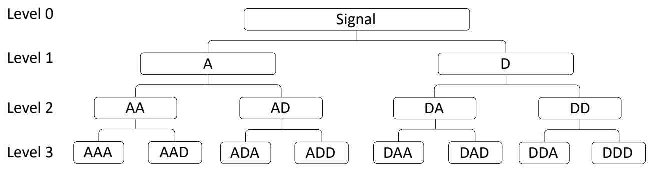

Fig. 3: Signal decomposition using wavelet packet transform (here with four levels, the leftmost branch corresponds to DWT decomposition).

decomposes both approximation and detail coefficients, leading to a tree structure with DWT as the left most branch, as shown in Fig. 3. This level of decomposition allows for higher compression, better denoising and feature extraction [28].

3. Approach

3.1. Concept

The aim of this study is to demonstrate a solution for online estimation of surface roughness and tool condition monitoring in milling operations as part of a modular retrofitting kit based on an edge device within the machine. The present implementation uses *Sinumerik Edge* as the edge device, therefore the program must be deployable to this device via the cloud-based IIoT (Industrial Internet of Things) platform *MindSphere*. The retrofitting kit relies on an internal Ethernet network within the machine to connect data sources to the edge device, thus a data logger is used to acquire analog data via the accelerometer's IEPE (Integrated Electronics Piezo-Electric) interface and transmit it to the edge device. Additionally, a web-based graphical user interface is implemented to provide the operator with machine data and surface roughness estimation values. The resulting system architecture is shown in Fig. 4.

The accelerometer should be mounted close to the tool centre point, in order to minimize errors due to damping of the vibration signal. Moreover, mounting the sensor has to be easy yet reliable, the structural integrity of the machine tool must not be compromised and the sensor and the necessary cabling must not interfere the operations. Therefore, the accelerometer is mounted on the spindle housing. In machines that already have an accelerometer within the spindle, the existing sensor could be used.

To process the signals, an algorithm based on wavelet packet transform is implemented due to its denoising property and its ability to extract features from non-stationary signals [29,30]. The algorithm requires only vibration data in order to minimise the effort for retrofitting older machines.

A deeper WPT enables a more precise isolation of individual frequency bands, while increasing computational cost. Here an eleven level-deep WPT is applied to the acceleration signal to obtain an adequately detailed decomposition. The packets with the highest energy are selected and used to reconstruct the signal. This yields high energy vibration at low frequencies, which includes tool vibration [31]. Subsequently, the reconstructed signal is integrated twice to obtain the deviation of the tool and peak values are used to estimate surface roughness. The root mean square value of the reconstructed signal is used to indicate tool wear.

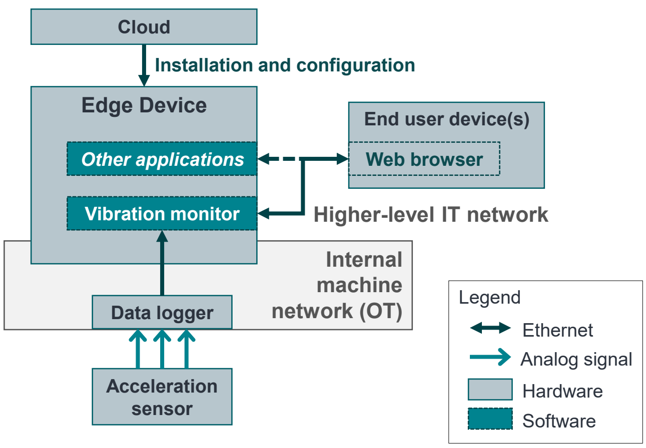

Fig. 4: System architecture

3.2. Experimental Setup

Experiments are conducted on a DMC 60H machining centre and vibration signals are captured by the triaxial accelerometer MMF KS943B.10, the mounting position and tool are shown in Fig. 5. Since the mounting surface does not coincide with the X-Z plane, the axes of the sensor do not correspond to the axes of the machine. As a result, the captured data has to be corrected by the projection of the angle. A face roughing operation is repeated until the inserts show significant wear. Each experiment consists of eight separate cuts (Fig. 6),

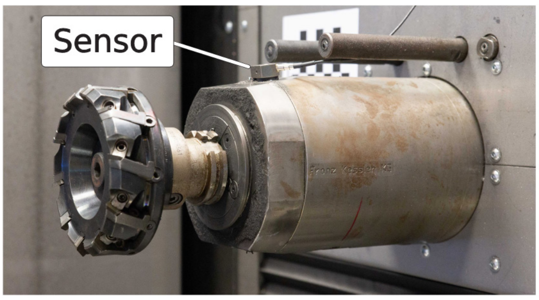

Fig. 5: Spindle, tool and sensor used in the experimental setup

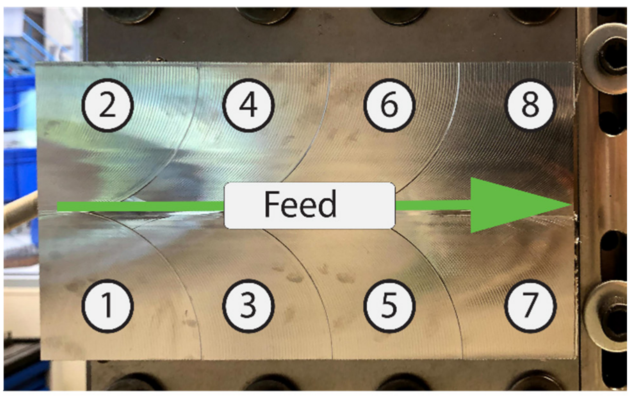

Fig. 6: Workpiece with overlay of milling passes and masurement points

alternating between the top and bottom of the workpiece. The cutting length per cut is limited to less than the diameter of the tool in order to eliminate recutting of the surface on the backstroke of the face mill, thereby facilitating consistent measurement. Neighbouring cuts are offset by 0.5 mm in Z direction. The inserts of the face mill are subject to non-negligible axial and radial runout deviations due to imperfect adjustment, resulting in a measurable surface roughness.

The feed rate is constant throughout the eight cuts of each individual experiment but is varied from on experiment to the next. The nominal rate of 1595 mm/min is reduced to 75% and eventually 50%, resulting in reduced surface roughness, then set to 100% again.

Surface roughness R_z is determined with the mobile roughness measuring instrument *Mahr MarSurf PS 10* at eight individual measuring spots, as shown in Fig. 6. At each individual point, three measurements are taken along the path of the tool centre point and the average is calculated. Table 1 contains further information on the equipment and experimental conditions.

Table 1: Experimental setup

Machining centre	DMC 60H
Tool	Face mill, ⌀ 125 mm 10 inserts
Machining parameters:	
a_p	$2\ mm$
n	$570\ rpm$
f	$797.5 - 1196.25 - 1595\ mm/min$
Workpiece material and dimension	Steel C45E (1.1191), $247\ mm$ x $130\ mm$
Sensor	MMF KS943B.10
Data logger	Measurement Computing WebDAQ 504
Roughness measurement	MarSurf PS 10

4. Results

The surface estimation algorithm consists of several steps. First a low-pass filter (anti-aliasing) is applied to the signal, then the component normal to the milling surface is obtained by taking the mounting position of the accelerometer into account. The high resolution decomposition resulting from the eleven-level-deep WPT allows for detailed selection of feature packets. The wavelet packet with the highest energy, “AAAAAAAADAA”, is selected. This packet contains the vibration at blade passing frequency (Fig. 7). After wavelet reconstruction, the signal is integrated twice to obtain spindle deflection and the rolling mean is subtracted to facilitate peak to peak calculation.

The results (Fig. 8) show that during travel and air cutting the estimated surface roughness is relatively low albeit not zero. This is due to changes in the direction and speed of travel and other causes of vibration such as tool imbalances. The estimated roughness at the start of recording shows a spike originating in rapid positioning of the spindle. The other experiments show similar signal patterns.

In Fig. 9 the measured roughness (average of three measurements) is plotted over the average output of the

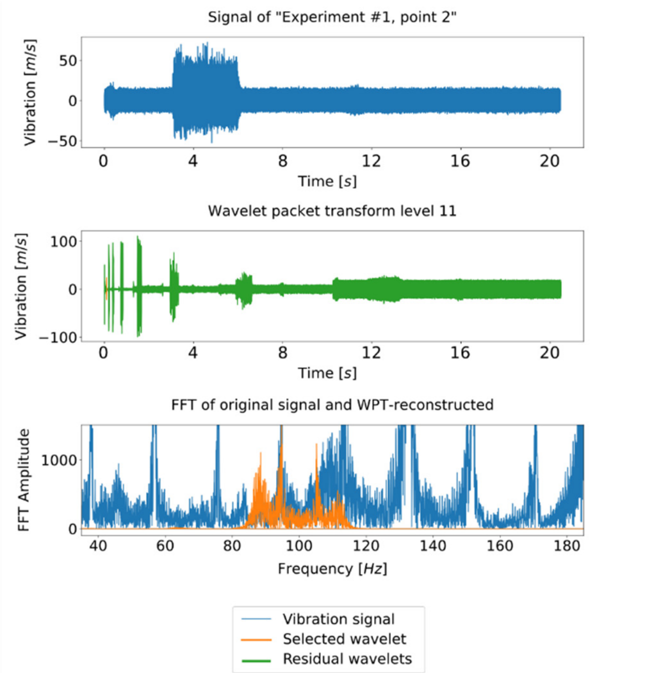

Fig. 7: Vibration data, WPT and FFT spectrum

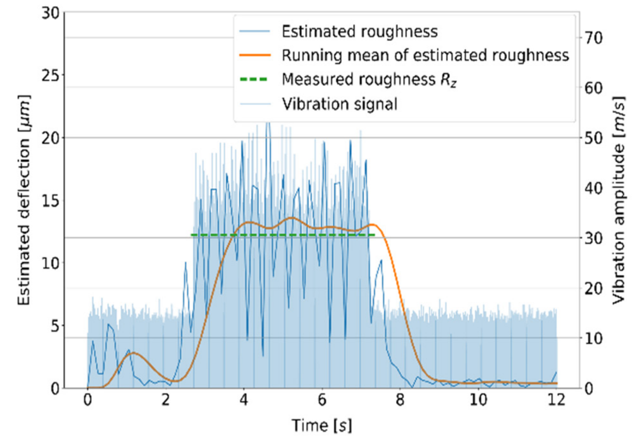

Fig. 8: Estimated and mean measured surface roughness

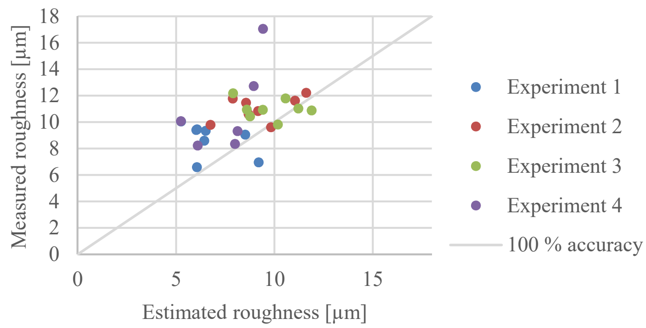

Fig. 9: Measured roughness and average estimation from the monitoring solution

roughness monitoring algorithm for each point considered in the experiments. The last experiment was aborted due to tool failure (broken inserts), therefore only yielding six points. The

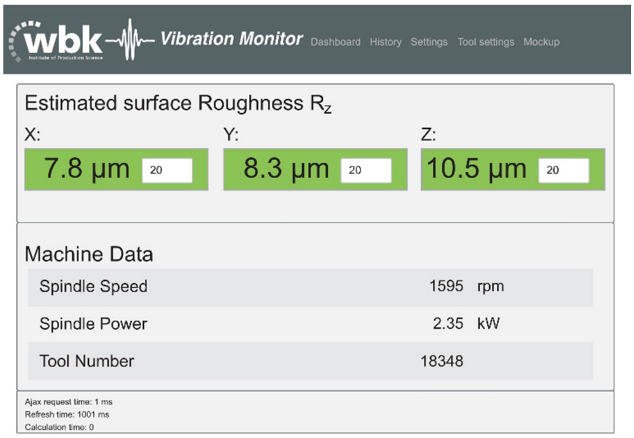

Fig. 10: Web-based user interface

largest estimation errors are observed in the last experiment, this may be due to the effect of tool wear (the inserts were chipped). Overall, the measurements correlate with the estimation but are somewhat higher. The static components of surface roughness due to tool geometry and runout cannot be entirely predicted based on the vibration, therefore a slightly greater roughness than predicted was expected.

The roughness estimate is displayed alongside other information in a live web-based dashboard (Fig. 10). By displaying the information from online monitoring during machining, the feedback loop for manual optimisation of process settings is significantly shortened compared to subsequent quality control after machining. The roughness estimation is displayed for all three directions, in order to enable the monitoring of a wide variety of machining processes without prior information about the relevant direction. Alternatively, additional information on the current tool and process could be acquired from the machine control unit or from process planning, however the additional interfaces required would increase the effort required for rolling out the monitoring system to a wide variety of machines.

During experiment 4 one or more of the inserts reached the end of the tool life and chipped. That in turn caused the failure of other inserts and lead to a halt of the spindle close to point 7. A closer analysis of the captured data reveals a large increase in vibration and in the predicted roughness due to damage to the inserts, approximately 0.5 s before failure (Fig. 11). This suggests the monitoring system could be used to stop the machine based on a threshold for detection of sudden increases in vibration, thus reacting faster than the integrated monitoring in the machine control unit and limiting potential damage to tool, workpiece, and machine.

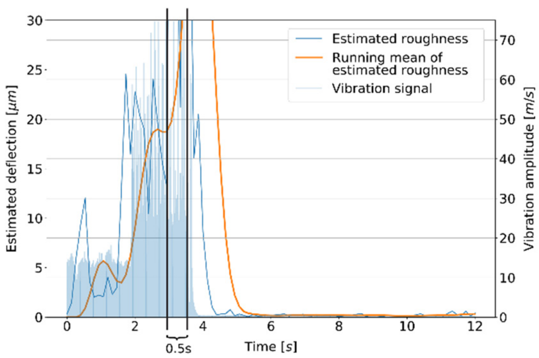

Fig. 11: Tool breakage and detection interval

5. Conclusion

Within the context of a retrofitting kit for Industry 4.0 solutions in machine tools, an edge application for vibration monitoring was developed. The application requires an accelerometer close to the tool centre point and is suitable for both new and existing machines. The application was developed and tested based on face milling experiments. Further work is needed to evaluate suitability for other milling processes.

The increased transparency and shortened quality feedback loop is a step towards optimising small series and single part manufacturing, which is especially relevant when considering the trend towards flexible mass customisation. A further step in this direction would be to collect historical data concerning cutting conditions on the one hand and vibration or (predicted) roughness on the other hand, in order to create data-driven models for predicting roughness from cutting conditions. In combination with vibration monitoring, this approach has the potential to bring the productivity in single parts manufacturing closer to the level achieved in highly optimised mass production.

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