

Real-Time Surface Roughness Analysis in Milling Using Acoustic Emission Signals for Industry 4.0 Applications [†]

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Abstract

In the expansion of Industry 4.0, many automation processes are being enhanced as means of accomplishing higher productivity goals. With the prospect of new achievable objectives, the demand for faster and more reliable resources processing methods are also needed. Similarly, machining processes have also been improved with the development of IoT devices by streamlining operations, enabling predictive maintenance, and providing real-time data for better decision-making, collaborating with such productivity levels. For instance, in metal milling, IoT-based sensors techniques are being developed and proved efficient in increasing speed and reliability, whereas reducing system invasiveness and complexity, which grants more profitability. The present paper proposes a real-time metal roughness average (Ra) analysis method based on Acoustic Emission (AE), which indirectly estimates roughness through signal processing and feature extraction of the EA signal through Power Spectral Density (PSD) evaluation. The experimental setting consists of a steel workpiece in which straight lines were milled with four distinct roughness levels (6 μm , 12 μm , 18 μm and 24 μm , produced by defined milling parameters), and the method was able to estimate the Ra with error under 7%. This work aims to contribute to the real-time monitoring of surface roughness in alignment with Industry 4.0 requirements, by demonstrating the effectiveness of IoT-based solutions, and the potential of Acoustic Emission in machinery sensing and process automation.

Keywords: milling; average roughness; real time applications; acoustic emission sensors; IoT sensor

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1. Introduction

The rise of the 4.0 industrial revolution fostered the development of strategies to improve the quality of industrial processes. One of them is Tool Condition Monitoring (TCM), which is the analysis of machine tool health by, for example, extracting signals and identifying patterns that indicate possible anomalies that could prejudice the machining process. Acoustic Emissions (AE) are described as the phenomenon of acoustic wave propagation caused by the sudden release of stress within a material subjected to

deformation, cutting, or fracturing [1], and can be employed in TCM through its sensing. AE signals are widely used mainly because of their ability to allow the detection of large energy discharges during plastic deformation, supporting close monitoring of cuts made in materials in the milling process [2]. In addition, the collected signals can also give information about the milling process, allowing the extraction of key performance indicators such as the surface finish quality of the fabricated products [3]. Surface roughness is considered a critical factor in evaluating the milling process, due to its inherent connection to factors such as functional performance, durability, and assembly compatibility of machined components [4]. Therefore, evaluating real-time surface roughness is important to improve process quality, which is paramount in the 4.0 industry context.

Approaches to analyse and estimate surface roughness were made by acquiring images and using them as inputs in Convolutional Neural Networks (CNNs) to predict surface roughness with a 3.6% mean error [5], and also using sound signals transformed into Mel-Frequency Cepstral Coefficients (MFCCs) in machine learning algorithms such as CNNs, Temporal Convolutional Networks (TCNs), Random Forests (RFs), and Support Vector Machines (SVMs) to classify the MFCC representations into predefined roughness categories, with the developed models successfully delimiting discriminative patterns [6]. Moreover, features extracted from real-time data acquired by a rotating dynamometer and an accelerometer were used to predict surface roughness. Real-time monitoring enhanced the surface roughness analysis accuracy by a mean of 2.53% [7].

Hence, considering the feasibility of analysing surface roughness with real-time monitoring, aligned with the effectiveness of AE signals in TCM, this research aims to develop a real-time AE-based metal roughness average (Ra) analysis method that could indirectly predict roughness through the AE signal processing and feature extraction. The experiments were conducted on a steel workpiece, on which straight lines were milled with one of four distinct theoretical roughness levels (6 μm , 12 μm , 18 μm , and 24 μm), produced by predefined milling parameters. Moreover, the signal processing and algorithm were developed in the Matlab software, with classification of the four roughness levels was achieved using features extracted from the AE signals of the milled lines, with the estimated Ra presenting an error lower than 10%. This work is innovative because it presents a method that analysed signals collected from an IoT sensor that has not been broadly used in other research and didn't use machine learning models to perform predictions, which reduced computational burden. It presents contributions to real-time roughness monitoring that align with Industry 4.0 requirements.

2. Methodology

2.1. Experimental Setup

The micromilling tests were carried out on a ROMI vertical CNC machining center model D600. A high-speed spindle NSK Nakanishi model NR3060S with a maximum rotation speed of 60,000 rpm was mounted on the machine tool, where a 500 μm diameter, solid carbide, TiAlN-coated, two cutting edges and helical flutes end mill was attached. Straight lines were milled in a 6 mm thickness steel workpiece, while the data was sampled at 1.11 MHz through a piezoelectric wireless AE sensor, coupled to the side of the workpiece and perpendicular to the milling spindle as in Figures 1 and 2.

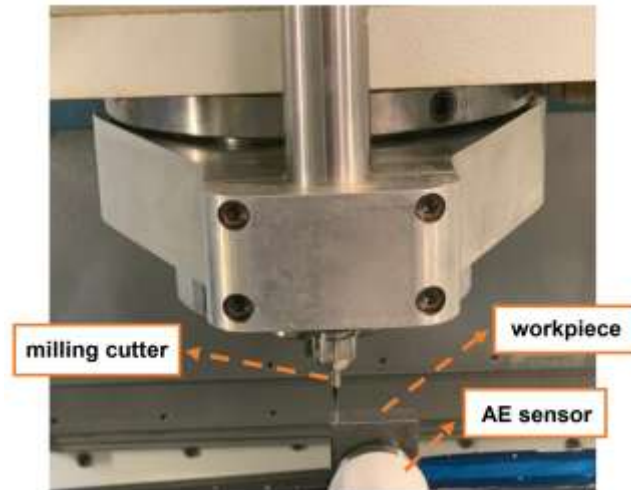


Figure 1. Acoustic Emission acquisition test bench.

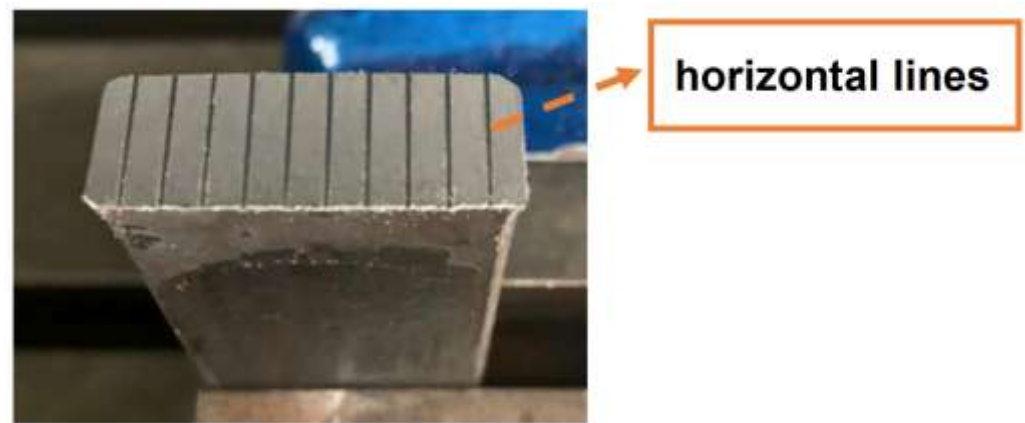


Figure 2. Steel workpiece after experimentation.

2.2. Theoretical Background

The roughness average of the surface in each line is dictated by either the end mill geometry and the process parameters, such as the milling feed rate, spindle speed, and cut depth [8,9]. By altering said parameters, it is possible to create different roughness values and AE responses, which may be processed and used as classification features [10]. The theoretical values were calculated using Equations (1) and (2) [11].

$$R_{max} = f_z \cdot \tan(x') \quad (1)$$

$$R_a = \frac{f_z \cdot \tan(x')}{4 \cdot [1 + \tan(x')]} \quad (2)$$

where R_{max} is the maximum roughness, R_a is the roughness average, f_z is the feed rate and x' is the secondary cutting edge angle.

2.3. Roughness Average Estimation Method with Acoustic Emissions

The IoT sensor stored the raw signal as vectors and then sent them to the computer via wi-fi, where they are converted into .mat files. In order to extract a characterizing feature, a PSD analysis was conducted through transforming the time-domain signal vector to the frequency domain using the Discrete Fourier Transform (DFT), followed by filtering with fifth order band-pass Butterworth filters.

The chosen parameter to estimate roughness levels was the RMS within selected frequency bands. The criteria to select a band is that it must contain a concentrated amount of energy, so that it has a larger signal-to-noise and carries relevant information, and also presents a distinct shape for each roughness level, enabling their identification. After several tests, it was noticed that the chosen parameter (band RMS) behaves as an S curve as the theoretical surface roughness increases, as represented in Figure 4.

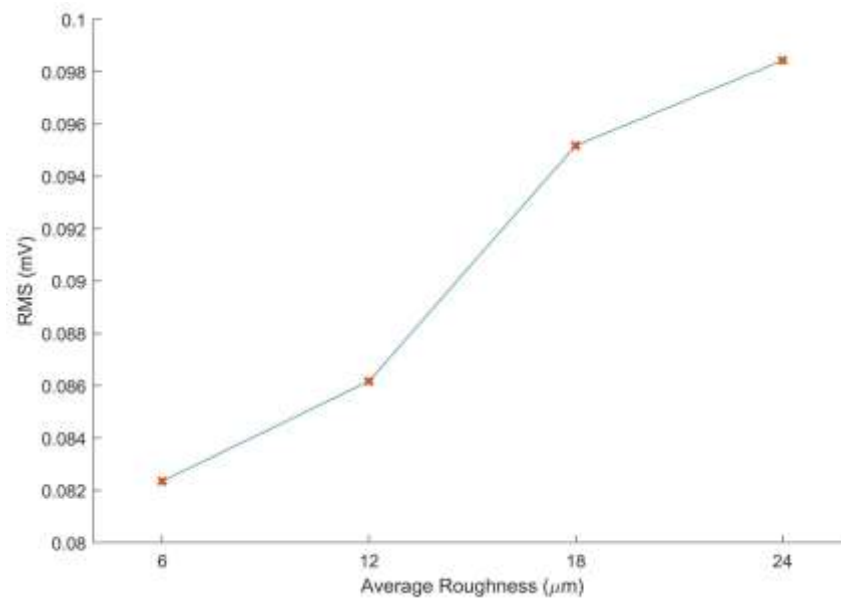


Figure 4. Typical RMS of a selected band.

The presented graphic in Figure 4 refers to the RMS of the full length signal vector, thus, in order to approach real time condition monitoring, the next step was to analyse time sections of the signal and verify if they behave similarly. Each signal was then segmented in 50, 20, 10, 5 and 1 ms windows (with an overlap of consecutive windows of 5%) and calculated the RMS of the 40–65 kHz band of each window individually.

3. Results and Discussion

The resulting filtered RMS of the windows were then organized into the graphics in Figure 5, and the Normalized Root Mean Squared Error (NRMSE) in Table 1. It was observed that the segments RMS's deviate around the RMS of the signal as a whole, and for bigger windows the more similar to it. This behaviour shows a tradeoff between the estimation method's accuracy, system burden and the speed at which the information is updated, since larger windows increases accuracy but reduces the data refresh rate, whereas higher sampling rate or a moving RMS window demands superior computational power. Also, it was noted that higher average roughness levels, also produce greater NRMSE, suggesting that this technique may have limitations in non micro milling operations.

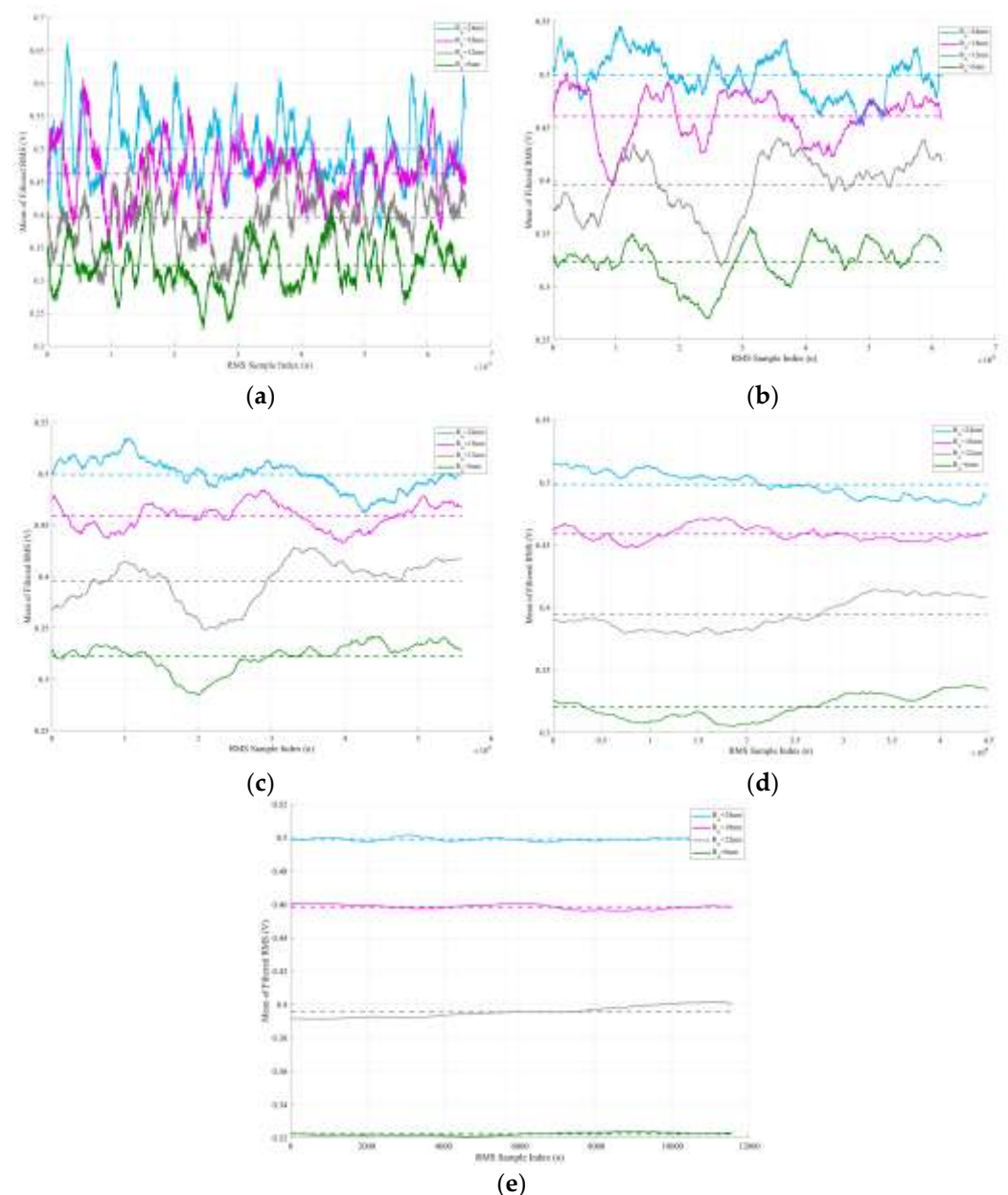


Figure 5. Filtered windows RMS for each size: (a) 1 ms; (b) 5 ms; (c) 10 ms; (d) 20 ms; (e) 50 ms.

Table 1. Roughness estimation RMS windows normalized root mean squared error (NRMSE).

RMS Window (ms)	6 μm	12 μm	18 μm	24 μm
50	0.08%	0.42%	0.59%	0.97%
20	1.23%	3.60%	5.10%	6.75%
10	2.93%	7.74%	10.88%	14.15%
5	6.39%	16.51%	23.38%	30.62%
1	17.20%	47.24%	70.43%	99.18%

4. Conclusions

This work presents a method for real-time metal roughness average analysis based on acoustic emission, aimed for Industry 4.0 IoT applications. The experimental setup was made on a vertical CNC machining center, where a steel workpiece was milled and the operation's acoustic waves were collected through a wireless sensor and sent for processing and PSD analysis in the Matlab software. The results validate the method's

capability of accurately estimating a surface's average roughness in real time scenarios (less than 7% NRMSE in some setups), with the benefits of lower computation requirements when compared to machine learning methods and the modularity benefits of IoT devices.

The information presented in this article aims to corroborate with Industry 4.0 development by contributing with a less complex, modular, faster and reliable approach, that collaborates with improved data collection and better decision-making targeting more economically and environmentally viable solutions.

Researchers of similar worklines are encouraged to test different experimental setups such as different machinery, workpiece materials and shapes, sensory systems and in the presence of factory floor noise, and it is also suggested a study of these methods optimization in factory applications.

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