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Comparative analysis of chatter detection approaches in micro-milling using force, vibration and acoustic monitoring

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Abstract

In milling processes, the selection of suboptimal process parameters can lead to the occurrence of regenerative chatter, a form of self-excited vibration. This phenomenon not only amplifies process forces but also accelerates tool wear, thereby diminishing the operational lifespan of the cutting tool. Additionally, these vibrations generate significant surface irregularities on the workpiece, which severely compromise surface finish quality—a critical aspect in precision machining. Given the significant influence of size effects and process damping, the prediction of dynamic behavior in micro-milling processes remains an active area of research. This highlights the necessity for online, sensor-based detection methods to minimize the negative effects of chatter. A primary challenge in employing sensors in micro-milling is the relatively low force magnitudes involved, which necessitate highly sensitive sensors. Achieving an adequate signal-to-noise ratio becomes increasingly difficult as milling dimensions decrease. In this study, three types of sensors—dynamometer, accelerometer and microphone—are utilized to gather data from micro-milling processes. The collected signals are subsequently analysed in both time and frequency domains to detect chatter. In the time domain, information regarding amplitude variations is extracted and two statistical indicators are compared. Fast Fourier Transform (FFT) is employed for frequency domain analysis. The results mark the capabilities and limitations of each sensor type, as well as the effectiveness of the chatter identification approach.

micro-milling, chatter detection, vibration monitoring, signal processing

1. Introduction

Preventing regenerative chatter vibrations is critical to mitigating their detrimental effects on surface quality, tool wear and machining productivity during milling operations. Although surface topography analysis offers precise chatter detection, its real-time application remains impractical. To address this, various sensors, such as dynamometers, accelerometers and acoustic emission sensors are employed to measure physical parameters like cutting forces, acceleration, and acoustic emission signals [1].

Dynamometers have limited frequency ranges, making them less effective for frequency analysis in micro-milling applications, where tools exhibit high natural frequencies. Accelerometers, offering a broader frequency range, are affected by noise levels that complicate their use in low-amplitude vibration environments like micro-milling. Acoustic emission sensors can capture high-frequency signals from 20 kHz to 1 MH, whereas microphones are effective in detecting audible frequencies below 20 kHz. A combination of different sensor types can enhance the chatter identification [1, 2].

Data acquired from sensors can be analyzed in both the time and frequency domains. In the time domain, statistical indicators such as mean, standard deviation, root mean square (RMS) and derived parameters from these are commonly utilized to identify chatter vibrations [3-5]. In the frequency domain, Fast Fourier Transform (FFT) and Power Spectral Density (PSD) are widely applied to identify frequency components linked to chatter vibrations [1, 6, 7]. Furthermore, FFT is frequently used to validate newly developed detection methodologies [1, 7, 8].

This study evaluates the effectiveness of three sensor types—dynamometer, accelerometer and microphone—for chatter detection. Data is analyzed in the frequency domain using FFT, while the suitability of two statistical indicators for assessing the stability conditions of micro-milling processes is examined in the time domain.

2. Methodology

2.1. Experiment Setup

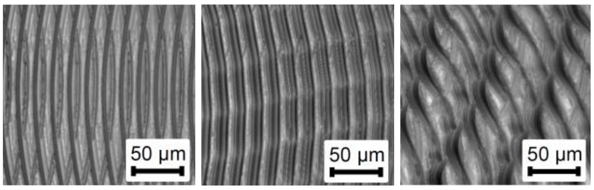
The milling experiments were conducted using a modified MMC-1100 milling machine from LT Ultra-Precision Technology GmbH. Two-Flute micro end mills with diameters of 1.2 mm with were used as cutting tools, which induce sufficiently large forces to be measurable with the available sensors.

A triaxial Kistler 9119AA1 multi-component dynamometer from Kistler Instrumente AG was directly mounted on the machine table to measure cutting forces. The workpiece was fixed using an adapter plate. A PCB Piezotronics 356A45 triaxial accelerometer, with a resonance frequency of 30 kHz, was attached to the adapter plate to capture vibrations. Additionally, the sound was recorded using the built-in microphone of a Xiaomi Mi 10T Lite smartphone. A comparison of the smartphone microphone's frequency response with a measurement-grade microphone featuring a constant linear frequency response revealed significant amplification in the range of 5 kHz to 9 kHz. However, these frequencies fall outside the tooth passing and chatter frequency ranges for this experiment and do not affect the results.

The workpiece material was RSA-501 aluminum alloy, produced by RSP Technology. This material has a chemical composition of AlMg5Mn1Sc0.8Zr0.4 and is characterized by its ultrafine grain structure, averaging less than 1 µm. This property enables high-precision surface machining [9]. The milling experiments were conducted using full immersion cutting.

2.2. Surface topography

The stability characteristics of milling processes were evaluated through the analysis of surface topography using the white light interferometer WYKO NT1100 from Veeco Instruments Inc.. Alongside clearly defined stable and unstable conditions, two transitional states were identified. In certain processes, subtle undulations were observed in the circular tool engagement marks, indicating the presence of slight but not fully developed chatter. Previous studies have similarly reported processes exhibiting mild chatter, which can be differentiated from fully unstable conditions based on the surface features of the workpiece [10, 11]. These stability states are illustrated in Figure ***1***, where n represents the spindle speed and a_p the depth of cut.



n = 30,500 min^{-1} a_p= 10 µm | n = 30,500 min^{-1} a_p= 50 µm | n = 30,000 min^{-1} a_p= 100 µm

Figure 1: White light interferometry images at 20x magnification, illustrating different stability states with a feed per tooth f_z = 10 µm

2.3. Frequency domain

Chatter frequencies were identified using FFT analysis of signals captured by both an accelerometer and a microphone. To distinguish frequencies associated with the cutting process from unrelated frequencies, signals recorded during tool engagement were compared to reference signals collected when the tool was not in contact with the workpiece.

Analysis with an accelerometer featuring a resonance frequency of 50 kHz revealed that the chatter frequencies for the tools used in this experiment did not exceed 15 kHz.

2.4. Time domain

The periodic sampling method introduced by Honeycutt and Schmitz [12] was utilized to identify the stability states of milling processes. In this approach, the measurement signal is sampled at intervals corresponding to a single tooth engagement. The stability indicator M is calculated as the average of the absolute differences between all adjacent sampling points, A_i and A_{i-1}, as defined in Equation (1) [12]. Here, N denotes the total number of sampled points. For stable cutting conditions, this indicator value approaches zero. In contrast, the presence of self-excited vibrations leads to an increase in this value.

$$M = \frac{\sum_{i=2}^{N} |A_i - A_{i-1}|}{N} \tag{1}$$

This method was applied to force, acceleration and acoustic signals. To mitigate the effects of tool runout, the stability indicator was recalculated using data sampled at intervals corresponding to one full tool revolution and then compared to results from the original sampling method.

3. Results

3.1. Frequency domain

FFT analysis of acceleration and acoustic signals revealed modulation within the chatter frequency range across all milling processes. In this analysis, the chatter signal acts as the carrier, while the periodic excitation or spindle rotation signal serves as the low-frequency informational signal.

Figure 2: illustrates the frequency-domain signals for three milling processes with distinct stability behaviors. The target tooth passing frequencies are 1000 Hz for the stable process and 1016.6 Hz for the other two processes, corresponding to spindle speeds of 30,000 rpm and 30,500 rpm, respectively.

In the stable process, harmonics of the tooth passing and spindle rotation frequencies are clearly visible in the acceleration data, distributed across the horizontal axis. A notable increase in excitation is observed at frequencies above 12 kHz, coinciding with the tool's natural frequency. In the sound signal, spindle-speed-dependent peaks are predominantly observed, with first harmonics below 4 kHz being particularly prominent. An amplitude increase between 6 kHz and 9 kHz is evident across all measurements, a characteristic feature of the microphone used.

In the unstable process, as expected, chatter frequencies are strongly pronounced in all signals, with amplitudes significantly higher than those of the tooth passing frequency. Peaks associated with chatter vibrations are modulated within the 10.5 kHz to 14.4 kHz range.

The third process represents a transitional phase with slight chatter. In the acceleration data, the chatter frequency at 13.3 kHz is distinctly visible with the highest amplitude, significantly exceeding that of the tooth passing frequency. This could lead to an erroneous classification of the process as unstable if only acceleration data were considered. However, in the acoustic signal, the chatter frequency is present, but its amplitude is lower than that of the tooth passing frequency. The highest peaks within the chatter frequency range are observed at 11.8 kHz and 12.3 kHz.

The analysis revealed that chatter frequencies in acceleration data are not reliable indicators of process instability in micro-milling, even when their amplitudes exceed those of the tooth passing frequency. Consequently, FFT analysis of acceleration signals alone proved to be insufficient for identifying stability behavior in micro-milling processes with such high chatter frequencies, given the limited frequency range of accelerometers. An alternative approach is to evaluate FFT results alongside time-domain signals, as amplitudes significantly increase during fully developed chatter vibrations [1].

For acoustic signals collected in this study, the ratio of the chatter frequency amplitude to the tooth passing frequency amplitude $\frac{A_{f_c}}{A_{f_a}}$ has been identified as a suitable stability indicator:

- Stable: $\frac{A_{f_c}}{A_{f_a}} = 0$ — No chatter frequency is present.
- Slight chatter: $\frac{A_{f_c}}{A_{f_a}} < 1$ — Chatter frequencies are present but have lower amplitudes than the tooth passing frequency.
- Unstable: $\frac{A_{f_c}}{A_{f_a}} \gg 1$ — Chatter frequency amplitudes significantly exceed the tooth passing frequency.

Rubeo and Schmitz [13] validated the applicability of this stability indicator for macro-milling processes, focusing on displacement, velocity, and acceleration data.

The microphone used in this study demonstrated a suitable frequency response for evaluating stability conditions. Unlike

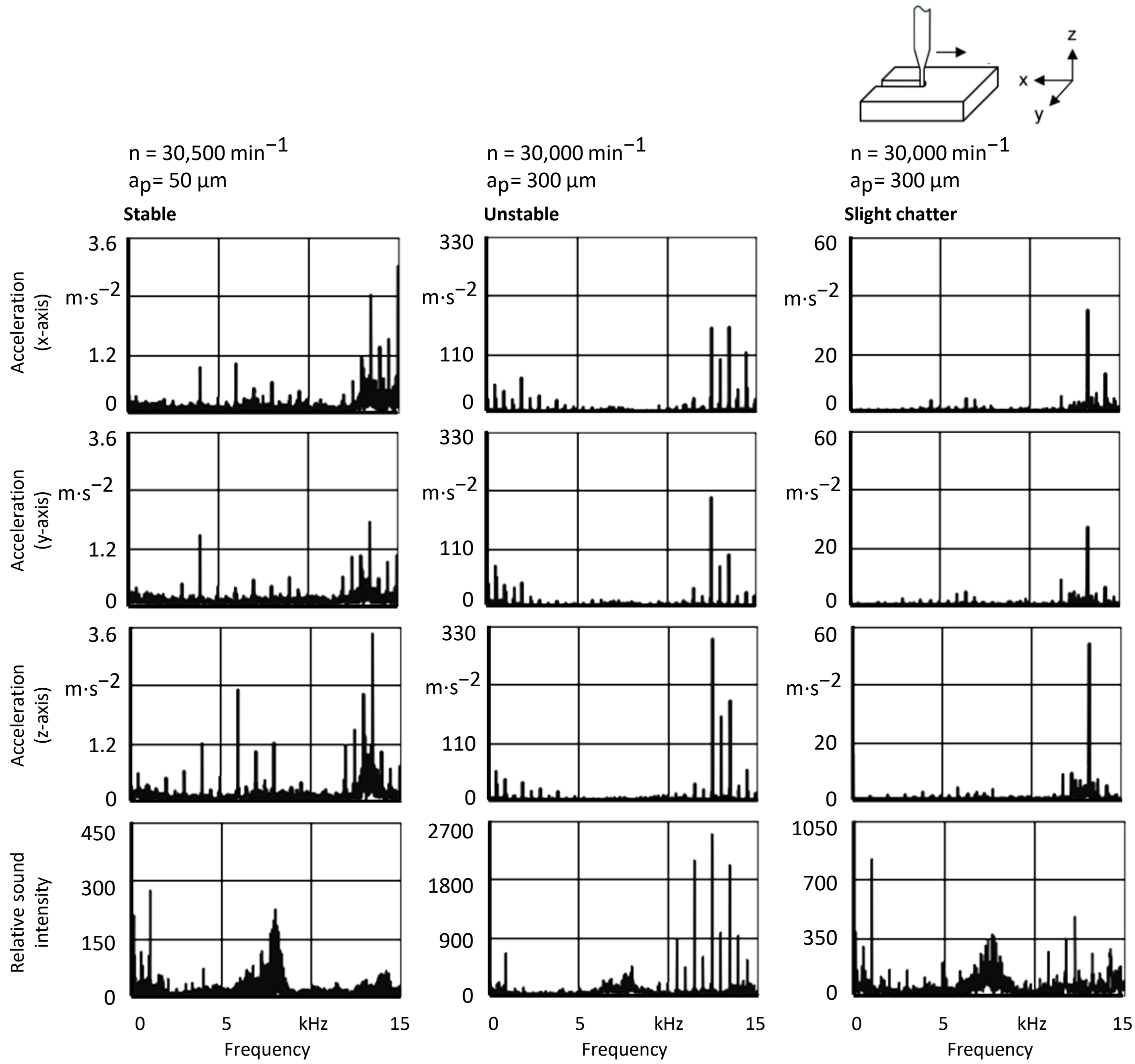


Figure 2: FFT of the recorded acceleration and sound signals for three different stability states with a feed per tooth f_z = 10 µm

acceleration data, acoustic recordings do not capture machine table vibrations and typically contain fewer harmonics of the tooth passing frequency. These harmonics generally exhibit lower amplitudes than the tooth passing frequency, enabling faster and more efficient identification of chatter vibrations.

3.2. Time Domain

Using the periodic sampling method, M-values were calculated based on the sampled measurement data from multiple milling processes. Figure 3 presents M-values sampled at the tooth passing frequency, while Figure 4 shows those sampled with a time interval corresponding to one full tool revolution.

When sampling at the tooth passing frequency, the M-values derived from acceleration data effectively distinguished between stable and unstable processes, with no overlap observed. However, these values were unable to differentiate stable processes from those with slight chatter. For force and acoustic signals, this sampling interval proved unsuitable, as the resulting M-values did not provide meaningful distinctions.

When sampling with a time interval of one full tool revolution, the force data showed a significant improvement in stability identification, with clear separation between stable and unstable processes and no overlap. However, the presence of slight chatter could still not be definitively identified.

For the acceleration data, the M-values obtained with this time interval allowed for a clear separation of the different stability behaviors, enabling precise identification of these states. In contrast, for acoustic signals, the M-values remained ineffective for identifying stability behavior, regardless of the sampling frequency used.

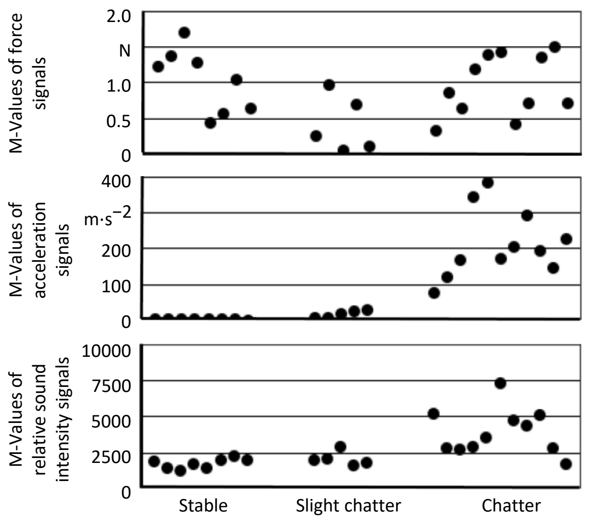


Figure 3: M-values for different signal types sampled at the tooth passing frequency. Process parameters: spindle speed ranging n = 15,000 min^{-1}

to 30,500 min^{-1}, depth of cut a_p = 50 µm to 600 µm, and feed per tooth f_z = 10 µm.

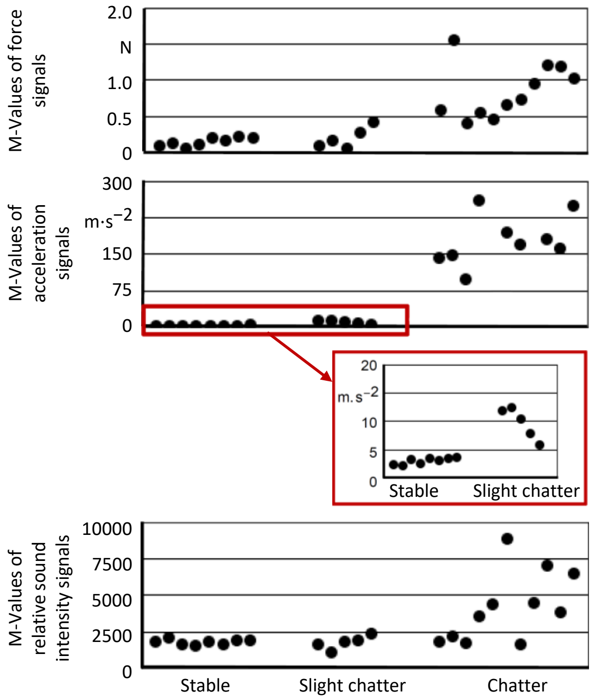


Figure 4: M-values for different signal types sampled at intervals of one tool revolution. Process parameters: spindle speed ranging n = 15,000 min^{-1} to 30,500 min^{-1}, depth of cut a_p = 50 µm to 600 µm, and feed per tooth f_z = 10 µm.

4. Conclusion

This study evaluated the effectiveness of dynamometers, accelerometers and microphones for in situ detection of chatter in micro-milling processes, focusing on both time-domain and frequency-domain analyses. The results demonstrate that while FFT analysis of acceleration signals provides insights into chatter frequencies, it is insufficient for reliably identifying stability states due to limitations in distinguishing between stable, transitional and unstable processes. In contrast, the ratio of chatter frequency amplitude to tooth passing frequency amplitude in acoustic signals proves to be a robust stability indicator, capable of differentiating between these states.

Periodic sampling methods further revealed that sampling at one tool revolution intervals improves stability identification for force and acceleration data. However, slight chatter remains challenging to identify with force data and acoustic signals are unsuitable for M-value analysis under these conditions. Overall, the combination of frequency and time-domain analyses, particularly leveraging acoustic signals, offers a promising approach for efficient and accurate chatter detection in micro-milling processes.

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