Advances in Computer, Signals and Systems (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/acss.2025.090312
ISSN 2371-8838 Vol. 9 Num. 3

Industry-Education Integration Case for AI+ Practical Teaching: Machine Tool Vibration Signal Recognition

Chunhua Feng[1,a,*], Jiaqi Chen[1,a]

[1]*School of Mechanical Engineering, University of Shanghai for Science and Technology, Shanghai, China*

[a]*fengchunhua333@163.com*, [b]*cjq15962899649@163.com*

**Corresponding author: Chunhua Feng*

Keywords: Industry-Education Integration, Vibration Signal Recognition, AI

Abstract: With the continuous and rapid development of artificial intelligence (AI) technologies, educators are increasingly faced with the pressing challenge of how to effectively incorporate AI into professional instruction. Using the course "Mechanical Testing Technology" as an example, this study investigates how AI techniques can be applied to analyze vibration signals from machine tools, adopting an approach that integrates academic instruction with industry practices. Vibration signals often display nonlinear and time-dependent behaviors due to multiple variables such as tool degradation, workpiece material differences, and variations in cutting conditions. In such intricate environments, artificial intelligence shows considerable promise. This study emphasizes key processes including the real-time collection, filtering, and noise reduction of vibration data, along with the evaluation of machine tool vibration conditions using both time-domain and frequency-domain analytical methods. It not only confirms the effectiveness of AI-based approaches in recognizing vibration patterns in machine tools but also provides valuable insights and practical references for future research and applications in this area.

1. Introduction

The identification of machine tool vibration signals is a critical component in achieving effective condition monitoring, fault diagnosis, and quality control during the milling process. To enhance students' understanding of the vibration characteristics of machine tools, this paper employs the identification of machine tool vibration signals as a case study. Due to the influence of intermittent cutting, milling vibrations exhibit nonlinear and time-varying behaviors, making them difficult to fully characterize using frequency domain analysis or empirical judgment alone [1]. Tool condition monitoring (TCM) typically employs a range of sensors for data acquisition and integrates systematic signal processing techniques to enable the early detection and identification of abnormal conditions, such as tool wear, chipping, and cutting instability [2]. The process mainly involves four steps: data collection, preprocessing, feature extraction, and state identification. A three-axis accelerometer is typically used for data collection during milling process monitoring. In the preprocessing stage, filtering, noise suppression, and normalization are performed to improve the signal-to-noise ratio. Time-domain and frequency-domain analyses, as well as time-frequency methods like the short-time

Fourier transform or wavelet transform, are used to capture dynamic characteristics across different time scales and frequency bands. Multi-scale feature extraction techniques based on wavelet transform and time-frequency spectrograms have proven effective in improving the detection of operational variations and early faults.

In recent years, significant advancements have been achieved in the application of artificial intelligence to vibration signal recognition. Through deep learning techniques, distinctive feature representations can be automatically extracted from raw signals or their associated time-frequency representations, enhancing both the accuracy of recognition and the model's adaptability in challenging real-world scenarios [3]. On the other hand, recent studies on the milling process show that applying time-frequency transformation to acoustic emission or vibration signals before inputting them into a deep learning model can effectively classify categories and detect anomalies in real-world data. This result demonstrates the effectiveness of an end-to-end strategy and highlights the successful combination of time-frequency analysis with CNN/LSTM models [4].

Based on this foundation, the milling machine is chosen as the research subject in this paper, and an integrated processing system is established, centered around experimental cases. The system encompasses stages including data acquisition, noise filtering, feature extraction, and condition identification. Its goal is to thoroughly assess the effectiveness of artificial intelligence in recognizing complex milling vibrations and to explore its potential applications.

2. Method for Identifying Vibration in Machine Tools

2.1 Model Development and Establishment

The vibrations generated during machining operations reflect the dynamic behavior of machine tools and provide important information about factors such as tool wear, workpiece material properties, and processing parameters. Abnormal vibrations often indicate unstable conditions, such as tool damage, loose fixtures, or chatter. For example, in high-speed milling, excessive spindle speed combined with loose tool mounting or machine oscillations can degrade workpiece surface quality, as shown in Figure 1. Accurate detection and analysis of vibration signals enable real-time monitoring of machine status, helping to avoid defects and mechanical failures.

In the milling process, vibration identification is crucial for several reasons. First, it supports tool condition monitoring and life prediction, improving tool efficiency. Second, it detects abnormal vibrations to provide early warnings of equipment failures, reducing downtime and maintenance costs. Third, vibration signal analysis enables adaptive control and machining parameter optimization, ensuring product surface quality and dimensional accuracy.

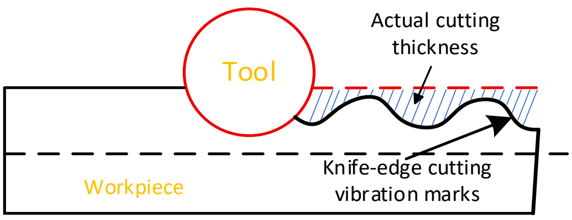


Figure 1: Tool cutting path

2.2 Vibration Identification Using AI

The typical procedure for identifying vibration signals in machine tools involves the sequence of "data collection - preprocessing - feature extraction - condition assessment." During the initial phase of signal acquisition and preprocessing, acceleration sensors are commonly employed to capture real-time vibration data generated during the milling process. Since raw signals are prone to interference from noise and process-related factors, techniques such as band-pass filtering, wavelet-based denoising, or empirical mode decomposition (EMD) are frequently applied to eliminate high-frequency noise and low-frequency drift, thereby enhancing signal quality and reliability.

Regarding feature extraction, time-domain techniques like standard deviation, peak-to-peak amplitude, and kurtosis provide a direct indication of vibration intensity and its fluctuation behavior. In the frequency domain, the Fast Fourier Transform (FFT) is employed to uncover energy distribution across specific frequency ranges, aiding in the detection of flutter and resonance effects. Additionally, time-frequency analysis approaches, including the Short-Time Fourier Transform and Continuous Wavelet Transform, enable the simultaneous characterization of temporal and spectral features across various scales. This dual capability makes them particularly effective for analyzing non-stationary vibration signals.

During the state recognition phase, time-domain analysis involves directly observing how the vibration signal's waveform evolves over time. It also incorporates an evaluation of amplitude, shape, and various time-domain features. On the other hand, frequency-domain analysis transforms the time-domain signal into a frequency spectrum using the Fast Fourier Transform (FFT). This allows the mixed vibration signals to be broken down into distinct frequency components, enabling precise localization of the fault source. The vibration signal identification process is illustrated in Figure 2.

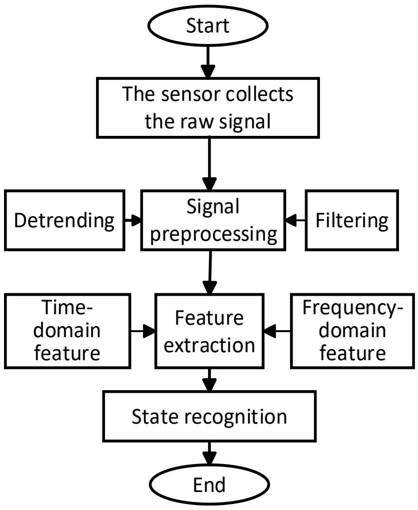


Figure 2: Vibration signal identification process

2.3 Experimental Simulation

The experimental design is illustrated in Figure 3. A three-axis acceleration sensor manufactured by Donghua Testing is attached to the machine tool spindle. One end of the sensor is linked to the DH5922D dynamic signal testing and analysis system from Donghua Testing. Subsequently, the DH5922D system is connected to a computer via a data transmission cable. Once the hardware connections are completed, the collected data is stored, analyzed, and processed using the accompanying DHDAS analysis software.

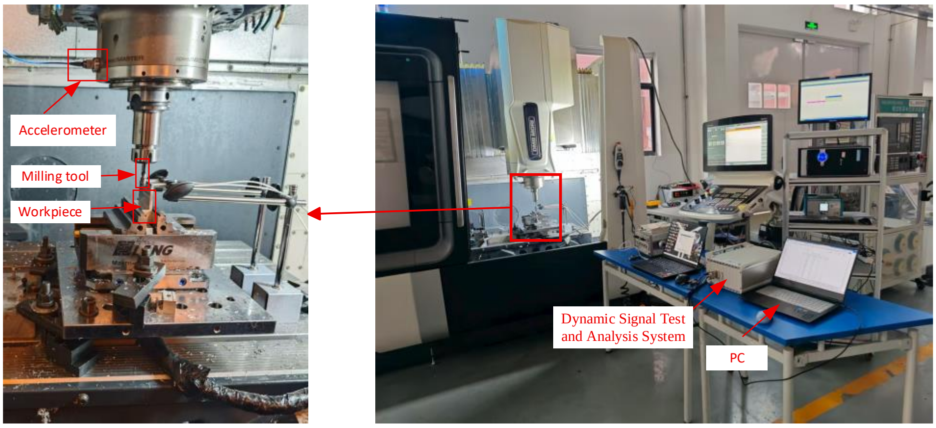
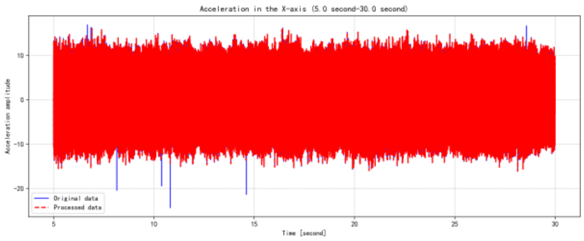
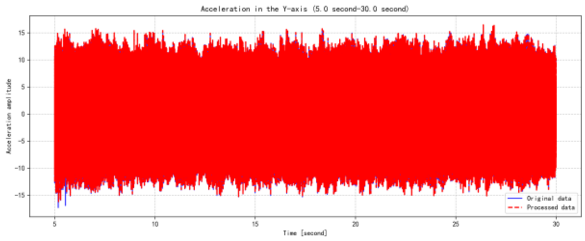


Figure 3: The experimental design

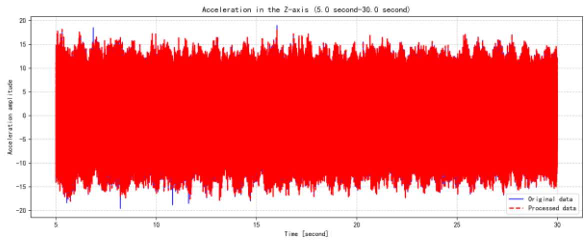
First, during signal acquisition, factors such as temperature-induced zero drift in the amplifier and slow thermal deformation of the sensor base can introduce a low-frequency "trend component" into the vibration signal. This trend has no physical meaning and can significantly reduce the accuracy of time-domain feature calculations, so it must be removed to eliminate baseline drift. Second, during data collection and transmission, signal errors may cause some data points to fall far outside the expected range. These outliers can distort statistical results and must be removed. Figure 4 shows the data after trend and outlier removal. The original data is shown with a blue solid line, and the processed data is shown with a red dashed line. After this preprocessing, the vibration data becomes more accurate and consistent.



a) X direction



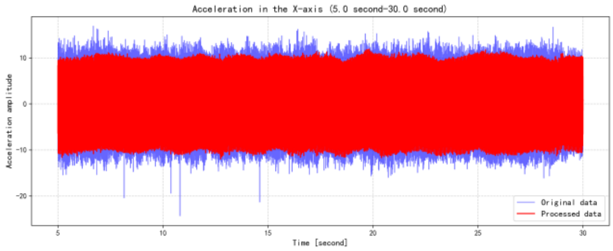
b) Y direction



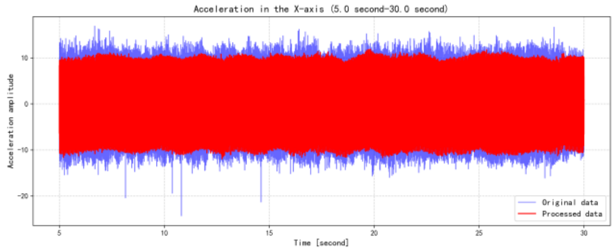
c) Z direction

Figure 4: The data after preliminary processing

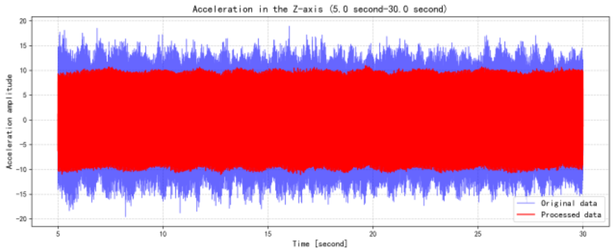
Secondly, since the experiment was conducted in a machining workshop, the sensor signals include not only the machine tool's own vibrations but also various interferences such as electromagnetic noise, power frequency disturbances, and vibrations from other equipment. These signals can mask early fault features or machining characteristics, leading to inaccurate analysis. Therefore, in addition to detrending and removing outliers, filtering is necessary. The filtered time-domain signal is shown in Figure 5, indicating effective noise reduction.



a) X direction



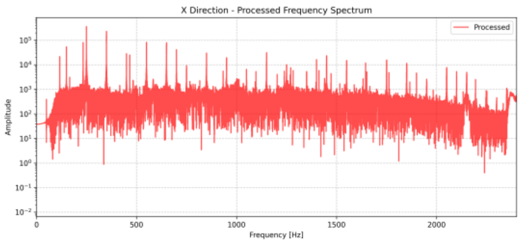
b) Y direction



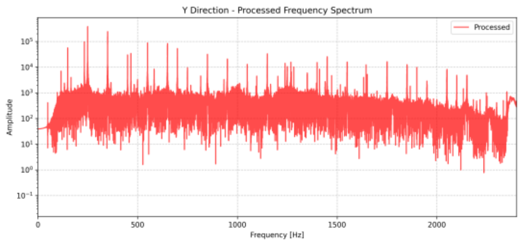
c) Z direction

Figure 5: Filtered data

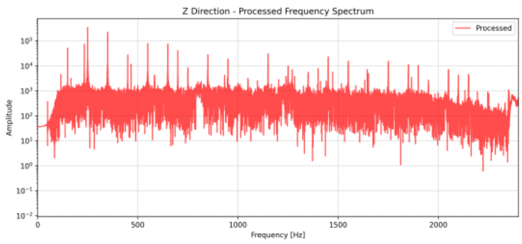
Subsequently, time-domain and frequency-domain evaluations of the filtered signal were conducted. Simultaneously, the FFT transformation was applied to generate the spectral diagrams across three axes, which are illustrated in Figure 6.



a) X direction



b) Y direction



c) Z direction

Figure 6: Spectrograms in three directions

As shown in Figure 5, the vibration signals in all three directions are not smooth but display tightly packed, high-frequency sawtooth oscillations. This suggests that the vibration stems from consistent high-frequency excitation, not random noise. The X and Y directions have similar vibration amplitudes, but their waveform details differ, reflecting the anisotropic dynamic behavior of the machine tool–workpiece system in radial response. Between 10 and 25 seconds, clear wave peaks and troughs appear in both directions, indicating amplitude modulation. This is typically caused by periodic changes in the thickness of the material being cut, which leads to variations in cutting force. Although the amplitude fluctuates over time, there are no signs of uncontrolled growth or sudden abnormal peaks, indicating a generally stable and controlled milling process. Notably, the Y direction shows more frequent and sharper wave peaks and troughs, suggesting greater sensitivity to cutting-induced excitation along this axis. The Z-direction vibration remains consistently low, likely due to the higher stiffness of the workpiece in that direction.

From the frequency domain perspective, Figure 6 shows clear spectral peaks at 150 Hz, 450 Hz, and 900 Hz across all three axes. In the X direction, vibration energy mainly concentrates at harmonic frequencies like 150 Hz and 450 Hz. The Y direction also shows peaks at these frequencies, but with higher overall amplitude and more high-frequency components between 1000–2000 Hz, suggesting lower stiffness and possible natural frequency excitation. In the Z direction, vibration becomes more noticeable near these frequencies due to the periodic impact of cutter teeth engaging and disengaging with the workpiece.

3. Conclusion

This study investigated the application of AI technology in analyzing machine tool vibration signals. A systematic analysis was conducted on the three-directional vibration signals during the milling process in both the time and frequency domains, thereby revealing the dynamic characteristics and primary sources of vibration. Spectrum analysis illustrated the distribution of vibration energy, confirming that the periodic cutting force generated by the spindle-tool system is the main source of machine tool vibration, rather than other mechanical components. The time-domain kurtosis values approached zero across all three directions, indicating the absence of significant impact components in the vibration signals. Furthermore, since no non-harmonic or discrete fault characteristic frequencies were observed in the spectrum, it was concluded that the machine tool operated stably during the monitoring period, with no typical localized faults, such as rolling element damage or gear tooth breakage, occurring. In conclusion, this article clearly elaborates on the industrial application scenarios, making the AI+ curriculum practice more tangible.

Acknowledgements

This research is funded by the Ministry of Education industry-university cooperative education project No. 231104429231321.

References

[1] Mohanraj, T., Shankar, S., Rajasekar, R., Sakthivel, N. R., & Pramanik, A. (2020). Tool condition monitoring techniques in milling process—A review. Journal of Materials Research and Technology, 9(1), 1032-1042.

[2] Hassan, I. U., Panduru, K., & Walsh, J. (2024). An in-depth study of vibration sensors for condition monitoring. Sensors, 24(3), 740.

[3] Chen, H. Y., & Lee, C. H. (2021). Deep learning approach for vibration signals applications. Sensors, 21(11), 3929.

[4] Umar, M., Siddique, M. F., Ullah, N., & Kim, J. M. (2024). Milling machine fault diagnosis using acoustic emission and hybrid deep learning with feature optimization. Applied Sciences, 14(22), 10404.