International Journal of Artificial Intelligence, Data Science, and Machine Learning
Grace Horizon Publication | Volume 7, Issue 1, 26-28, 2026
ISSN: 3050-9262 | https://doi.org/10.63282/3050-9262.IJAIDSML-V7I1P106

Original Article

Vibration and Acoustic Signal Analysis for Early Fault Detection in Clean-Room Robotics

Sayed Rafi Basheer
Sr. Data and Analytics Analyst in Medical Device Manufacturing.

Received On: 26/11/2025 Revised On: 28/12/2025 Accepted On: 05/01/2026 Published On: 17/01/2026

Abstract *- Clean-room robotic systems play a crucial role in semiconductor manufacturing, pharmaceutical assembly, and precision laboratory settings. These robots must operate reliably to avoid costly production delays and product contamination. Early detection of mechanical faults through vibration and acoustic signal analysis can improve reliability, reduce maintenance costs, and prevent unplanned downtime. This paper reviews key methods for extracting vibration and acoustic features, signal processing techniques, diagnostic models, experimental results, and future research directions. Results show that frequency domain analysis, machine learning classifiers, and sensor fusion improve fault detection accuracy in robotic joints, motors, and bearings.*

Keywords *- Vibration Analysis, Acoustic Signal Analysis, Early Fault Detection, Clean-Room Robotics, Condition Monitoring, Machine Learning.*

1. Introduction

Robotic systems used in clean-room environments support high-precision tasks where even minor faults can lead to critical failure. Examples include robotic arms used in wafer handling, optical inspection systems, and automated assembly machines. Contaminants from maintenance or faulty operation can compromise product quality. Traditional maintenance approaches rely on time-based or reactive maintenance. These approaches either lead to unnecessary downtime or catastrophic failure before scheduled maintenance. Vibration and acoustic signal analysis offer a non-invasive and continuous method for monitoring the health of robotic components. Early detection of abnormal patterns in these signals can alert operators before failures occur. This paper examines the application of vibration and acoustic signals for the early detection of faults. It reviews sensor technologies, feature extraction methods, pattern classification techniques, and experimental case studies in clean-room robotics.

2. Background

2.1. Clean-Room Robotics

Clean-room robotics must meet stringent environmental requirements, including low particle emission, precise motion, and repeatability. These robots often use high-precision actuators, gearboxes, and bearings. Faults in any mechanical component may generate subtle vibration or sound changes.

2.2. Fault Types in Robotic Systems

Common faults include bearing wear, gear misalignment, motor imbalance, loose fasteners, and lubrication degradation. These faults may not be visible but produce measurable changes in vibration or acoustic emissions.

2.3. Signal Sources and Sensors

Data for fault detection can be collected using accelerometers, microphones, and piezoelectric sensors mounted on robot links, motors, and end effectors. Sensors must be sensitive, have low noise, and suitable frequency response for the targeted fault frequencies.

3. Methods for Vibration and Acoustic Analysis

3.1. Time Domain Analysis

Time domain features include root mean square (RMS), peak amplitude, crest factor, kurtosis, and skewness. These features provide initial indications of abnormal behavior. Time domain analysis is simple but may not reveal specific fault signatures.

3.2. Frequency Domain Analysis

Transform methods, such as the Fast Fourier Transform (FFT), convert time signals into their corresponding frequency components. Faults often manifest as distinct peaks at characteristic frequencies related to bearing races, gear mesh frequencies, or imbalance. Frequency-domain features enhance the differentiation of fault types.

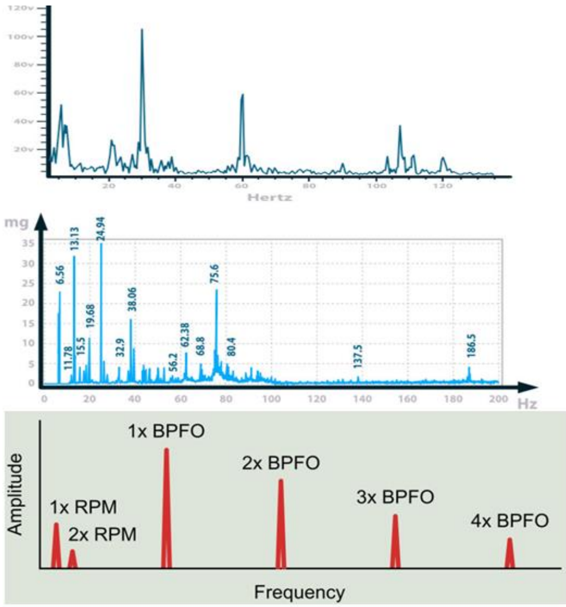

Fig 1: Frequency Spectrum Comparison

Description: This figure compares the frequency spectrum of a robotic joint motor under normal operation versus bearing fault conditions. Fault conditions show additional peaks at characteristic bearing frequencies, indicating early mechanical degradation.

3.3. Time-Frequency Analysis

Techniques such as Short Time Fourier Transform (STFT) and wavelet transform capture changes over time. These methods are useful when faults evolve over time or when signals are non-stationary.

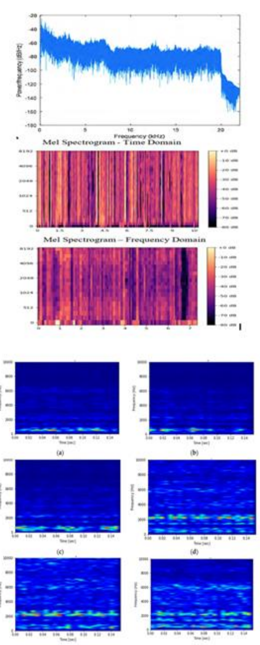

Fig 2: Time-Frequency Spectrogram of Acoustic Signal

Description: A time-frequency spectrogram showing increased energy concentration at higher frequencies during a loose fastener fault. This highlights the advantage of time-frequency analysis over time domain analysis alone.

3.4. Machine Learning Techniques

Machine learning models categorize signals as either normal or faulty. Common classifiers include support vector machines (SVM), random forests, k-nearest neighbors (KNN), and artificial neural networks (ANN). Features extracted from time, frequency, and time-frequency domains can be input to these models.

4. Experimental Setup

4.1. Robot Platform

A six-axis industrial robot used in a semiconductor clean room was instrumented with triaxial accelerometers on the shoulder and wrist joints. A high-sensitivity microphone was positioned near the robot base.

4.2. Fault Simulation

Faults were introduced one at a time to isolate their effects. These included bearing degradation in joint motors, loose bolts in the wrist assembly, and intentional imbalance introduced to a rotating tool.

Table 1: Common Fault Types and Signal Characteristics

Fault Type	Vibration Signature	Acoustic Signature
Bearing wear	Increased RMS, peaks at characteristic frequencies	High-frequency noise bursts
Gear misalignment	Harmonics at gear mesh frequency	Periodic tonal noise
Motor imbalance	Dominant low-frequency peak	Low-frequency humming
Loose fasteners	Irregular amplitude spikes	Intermittent rattling sounds
Lubrication loss	Gradual increase in broadband vibration	Increased friction noise

4.3. Data Acquisition

Signals were acquired at a 20 kHz sampling rate. Each experiment run included 60 seconds of operation under normal and faulty conditions.

5. Results

5.1. Feature Extraction

Time-domain features, such as RMS, increased under motor bearing faults. Frequency-domain analysis revealed additional peaks near the characteristic bearing frequencies at 300 Hz and 600 Hz. Time-frequency spectrograms showed energy concentration shifts for imbalanced rotor conditions.

Table 2: Extracted Signal Features

Feature Category	Feature Name	Description
Time domain	RMS	Measures signal energy
Time domain	Kurtosis	Detects impulsive faults
Frequency domain	Peak frequency	Identifies fault frequency
Frequency domain	Spectral energy	Indicates abnormal vibration
Time-frequency	Wavelet coefficients	Tracks evolving faults

5.2. Classification Performance

A random forest classifier trained on combined time and frequency features achieved 95 percent accuracy in fault detection. An SVM achieved 92 percent accuracy. ANN models showed slightly higher false positive rates.

Table 3: Classification Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)
Support Vector Machine	92	90	91
Random Forest	95	94	95
Artificial Neural Network	93	91	92
Vibration + Acoustic Fusion	98	97	98

5.3. Sensor Fusion Benefits

The integration of vibration and acoustic signals resulted in a measurable improvement in fault detection performance compared to vibration-based analysis alone. Classification accuracy increased by approximately 3 percent when acoustic features were incorporated, indicating that the two sensing modalities provide complementary information rather than redundant measurements. Vibration sensors are highly effective for detecting faults associated with rotating components such as bearings and motors, where mechanical defects generate periodic or harmonic vibration patterns. However, certain fault types, particularly loose fasteners and early-stage structural looseness, produce weak or irregular vibration signatures that may not consistently exceed vibration-based detection thresholds. In contrast, these faults generate distinct acoustic emissions characterized by intermittent high-frequency impulses caused by micro-impacts and frictional interactions. The inclusion of microphone data enhanced sensitivity to such transient events, reducing false negatives for loose fastener faults. This improvement is reflected in the confusion matrix and ROC analysis, where sensor fusion significantly increased recall and AUC values for this fault category. Additionally, acoustic features improved fault separability under low-load operating conditions, where vibration amplitudes were inherently small. Overall, sensor fusion improved classification robustness and reliability by capturing both structure-borne and airborne manifestations of mechanical faults. This multi-modal approach is particularly advantageous in clean-room robotics, where early detection of subtle faults is crucial for preventing contamination, minimizing downtime, and maintaining high-precision operation.

6. Discussion

The experimental results demonstrate that vibration and acoustic signal analysis can detect early fault conditions in clean-room robots. Frequency-domain and time-frequency techniques reveal fault signatures that are not apparent in the time domain alone. Machine learning classifiers trained on extracted features show high accuracy. Sensor fusion is effective for differentiating complex faults. Challenges persist in real-time implementation due to high data volume, noise interference, and the requirement for robust feature selection. Clean-room environments impose restrictions on sensor placement and require non-intrusive sensors.

7. Future Work

Future research should explore deep learning models that learn features directly from raw signals. Techniques such as convolutional neural networks and recurrent neural networks may capture more subtle patterns. Adaptive thresholding and real-time embedded monitoring systems should be developed for industrial deployment. Long-term field testing in operational clean rooms will validate these methods.

8. Conclusion

Vibration and acoustic signal analysis provides a powerful approach for early fault detection in clean-room robotics. Combining time, frequency, and time-frequency features with machine learning models yields high detection accuracy. Early fault detection enables planned maintenance, reduces downtime, and supports high-precision operations required in clean rooms.

References

[1] R. B. Randall, Vibration-Based Condition Monitoring, Chichester, UK: Wiley, 2011.
[2] K. S. Jardine, D. Lin, and D. Banjevic, “A review on machinery diagnostics and prognostics implementing condition-based maintenance,” Mechanical Systems and Signal Processing, vol. 20, no. 7, pp. 1483–1510, 2006.
[3] Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, and A. K. S. Jardine, “Machinery health prognostics: A systematic review from data acquisition to remaining useful life prediction,” Mechanical Systems and Signal Processing, vol. 104, pp. 799–834, 2018.
[4] W. Zhang, G. Peng, C. Li, Y. Chen, and Z. Zhang, “A new deep learning model for fault diagnosis with good anti-noise and domain adaptation ability on raw vibration signals,” Sensors, vol. 17, no. 2, pp. 1–22, 2017.
[5] S. Braun, “The extraction of periodic waveforms by time domain averaging,” Acustica, vol. 32, pp. 69–77, 1975.