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Application of Acoustic Signal Processing Techniques

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تطبيق تقنيات معالجة الإشارات الصوتية

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Abstract:
Industrial machinery produces complex acoustic emissions composed of overlapping tonal, broadband, and impulsive components. To diagnose mechanical conditions, predict faults, and guide noise control, one must go beyond simple SPL measurements and apply advanced processing. This work presents a comprehensive methodology combining **acoustic calibration**, **real-time spectral acquisition (Spectra LAB)**, and **post-processing in LabVIEW** for waveform reconstruction, power spectrum estimation, autocorrelation analysis, and advanced spectral decomposition. We integrate modern techniques such as **time–frequency clustering** and **model-based signal decomposition** to separate overlapping sources under industrial noise conditions. Case studies on lathe, drilling, cigarette, and packaging machines illustrate how these tools uncover subtle acoustic signatures, support fault detection, and enable condition monitoring. The results confirm that properly calibrated, software-based DSP is a powerful, non-intrusive diagnostic method in noisy industrial settings.

Keywords: Acoustic signal processing, calibration, FFT, autocorrelation, clustering, spectral decomposition, industrial diagnostics, predictive maintenance, nonstationary signal analysis.

الملخص
تُنتج الآلات الصناعية انبعاثات صوتية معقدة، تتألف من مكونات نغمية متداخلة ونطاق عريض ومكونات نبضيه. ولتشخيص الحالات الميكانيكية، والتنبؤ بالأعطال، وتوجيه التحكم في الضوضاء، لا بد من تجاوز قياسات مستوى ضغط الصوت البسيطة وتطبيق تقنيات المعالجة المتقدمة (SPL)، يُقدم هذا البحث منهجية شاملة تجمع بين المعايرة الصوتية والاكتساب الطيفي في الوقت الفعلي (Spectra LAB)، والمعالجة اللاحقة في (LabVIEW) لإعادة بناء الشكل الموجي، وتقدير طيف القدرة، وتحليل الارتباط الذاتي، والتحليل الطيفي المتقدم . حيث نقوم بدمج التقنيات الحديثة مثل التجميع الزمني-الترددي والتحليل النموذجي للإشارات لفصل المصادر المتداخلة في ظروف الضوضاء الصناعية. اجريت هذه الدراسة على المخرطة، وآلات الحفر، وآلة تعبئة وتغليف السجائر، كيف تكشف هذه الأدوات عن السمات الصوتية الدقيقة ، ودعم اكتشاف الأعطال، وتمكين المراقبة الحالة . وتؤكد النتائج أن معالجة الإشارات الرقمية (DSP) القائمة على البرمجيات والمعايرة بشكل صحيح تُعد طريقة تشخيص قوية وغير متطفلة في البيئات الصناعية الصاخبة.

الكلمات المفتاحية: معالجة الإشارات الصوتية، المعايرة، تحويل فورييه السريع (FFT)، الارتباط الذاتي، التجميع، التحليل الطيفي، التشخيص الصناعي، الصيانة التنبؤية، تحليل الإشارات غير المستقرة.

1. Introduction

In modern factories, multiple machines run simultaneously, each contributing to a complex soundscape. Acoustic emissions are not merely nuisances: they encode rich information about mechanical health, alignment, imbalance, gearing, and tool condition. However, raw audio contains mixtures of sources, reflections, and background noise.

A mere overall sound level reading fails to reveal which machine or component is responsible for a particular tonal or transient signature. To extract meaningful diagnostics, acoustic signal processing techniques are essential. By capturing raw sound data and applying digital transforms and statistical methods, engineers can separate overlapping contributions, characterize periodic behaviour, and detect anomalies early. Tools such as Spectra LAB used during acquisition and LabVIEW used for flexible post-processing provide a powerful platform for these tasks. Recent advances-in clustering, model-based decomposition, and data-driven diagnostics-enhance the capabilities further. This paper aims to present a detailed pipeline for applying these techniques in real industrial conditions. We emphasize calibration to ensure measurement fidelity, real-time spectral acquisition to guide sensor placement, and robust post-processing to decompose and interpret signals. Through extended case studies, the work demonstrates how acoustic processing can become a core component of condition monitoring in production environments.

2. Literature Review

Acoustic signal processing has matured in recent years, blending classical DSP with machine learning and physics-based modelling. A key trend is the transition from knowledge-driven to data-driven methods (Pan, 2025) which classify, filter, and separate acoustic sources using statistical learning paradigms. [5] Model-based decomposition has also gained attention: for example, in Decomposing and Modeling Acoustic Signals to Identify Faults, Pichler et al. (2025) formulate mechanical fault emissions as exponentially decaying oscillations, and use generalized likelihood ratio tests (GLRT) to detect them under high noise backgrounds, outperforming purely feature-based methods.

Clustering in time–frequency space is a powerful technique to disentangle overlapping sources. Drewnicka et al. (2025) introduced a DBSCAN-based method to cluster spectrogram bins and isolate fault-related harmonics in non-Gaussian interference. [0academia13] In industrial domains, graph-based feature extraction has also been proposed (Dobján et al., 2017) to represent spectral relationships robustly and improve classification accuracy. Beyond clustering, modern denoising architectures such as transformers and autoencoders (Chen et al. 2023, Yurdakul et al. 2023) have shown effectiveness in cleaning mechanical/acoustic signals while preserving diagnostic content. For instance, transformer-based models have been applied in vibration denoising, and deep networks adapted to acoustic classification of faulty machines reach high accuracies in real-world noisy conditions (Yurdakul & Tasdemir, 2023). Finally, nonstationary and nonlinear signal decomposition tools—such as the Hilbert–Huang Transform (HHT) and Empirical Mode Decomposition (EMD)—allow instantaneous frequency analysis of dynamic signals, making them suitable for complex machinery sounds whose spectral content shifts over time (e.g. during load changes). These methods complement Fourier analysis, particularly for transient events. From this literature, the best results often emerge from hybrid pipelines that combine calibration, real-time FFT, clustering, model-based decomposition, and learning-based denoising.

3. Methodology

In our methodology, calibration precedes any measurement, ensuring that recorded digital values map faithfully to physical acoustic pressure. Initially, a test signal generator produces pure tones at frequencies such as 100 Hz, 200 Hz, 500 Hz, 1000 Hz, and 2000 Hz. These tones are emitted via a loudspeaker in a low-noise environment and recorded through the same microphone–sound card chain used in machine testing. From these calibration signals, frequency response curves are derived and any gain offsets or non-linearities are corrected. The maximum deviation in frequency response was kept under ±1 Hz, and amplitude error under ±0.5 dB.Following calibration, actual acoustic measurements are acquired from target machines. The microphone samples at 44.1 kHz to preserve fidelity of harmonics and higher-order frequencies. Spectra LAB conducts real-time FFT and displays instantaneous spectral content, aiding sensor placement, orientation, and identifying dominant frequencies on the fly. These live spectra guide adjustments to microphone position to maximize signal-to-noise ratio of machine components of interest.

Recorded waveforms and spectral snapshots are exported to LabVIEW for deeper processing. In LabVIEW, three parallel analyses are performed: (i) reconstruction of the time-domain waveform with windowing and overlap, allowing visualization of amplitude oscillations and transient spikes; (ii) computation of **power spectral density (PSD)** using Welch's method with window averaging to reduce variance; and (iii) **autocorrelation** of segments to detect repeating periodicities corresponding to rotating or impact cycles.

To disentangle overlapping sources, we compute the **spectrogram (short-time Fourier transform, STFT)** and represent each time–frequency bin as a feature vector (e.g. amplitude, local slope, variance). These vectors feed a **DBSCAN clustering algorithm** (as per Drewnicka et al.) to group bins having similar spectral behavior. The resulting clusters typically correspond to motor harmonics, gear meshing frequencies, or intermittent tool impacts. For enhanced separation, we may apply **model-based decomposition**: e.g. fitting decaying sinusoidal models to clusters suspected of fault emissions (inspired by Pichler et al.). Finally, by re-mapping clusters back into the time and spectral domains, we quantify each source's share in energy (in dB or percentage) and analyze temporal fluctuations (e.g. cluster drift or amplitude modulation) as indicators of mechanical behavior or fault progression.

To reinforce robustness, we perform **parameter sensitivity tests** (varying clustering epsilon, FFT window size, overlap) and **cross-validation** (comparing results from alternate windows and segments). Consistency across parameter sets increases confidence in interpretations. This integrated pipeline—from calibration, acquisition, spectral/time-domain processing, clustering, to model fit—provides a rich, multi-perspective view into machine acoustics, suitable for industrial diagnostic use.

4. Results & Discussion

The extended results reveal nuanced insights into machine acoustic behavior. In the **lathe**, the 897 Hz harmonic dominated the spectrum with a sharp peak, and autocorrelation showed a strong periodicity ($r \approx 0.92$) repeating each spindle revolution. Clustering segregated this harmonic cluster distinctly from broadband machine noise and tool chatter. Interestingly, there was a small cluster around 450–500 Hz that gradually drifted in frequency over time—a possible sign of bearing or coupling wear.

In the **drilling machine**, the 183 Hz fundamental plus its harmonics were clearly separated. A distinct cluster containing high-frequency bursts (above 2 kHz) corresponded to transient drilling impacts and occasional chip collision events. Autocorrelation of that cluster revealed cycles approximately matching the spindle feed cycles.

The **packaging machine** showed dual behavior: a stable cluster near 500 Hz (motor) and a low-frequency pulsed cluster at ~0.6 Hz (cutter). Notably, the pulsed cluster displayed increasing amplitude variance during production ramp-up, possibly indicating slight mechanical lag or pneumatic pressure variation. In the **cigarette production** machine, motor harmonics at ~48 Hz dominated, but clustering revealed overlapping contributions from roller and feed mechanisms at ~150 Hz. The cluster mapped to rollers drifted subtly in frequency over minutes, perhaps due to paper tension variation.

Below is a more detailed and enriched version of the results table:

Machine	Dominant Frequency(s)	Peak Power (dB)	Autocorrelation r	Notable Clusters / Features	Observations & Implications
Lathe	897 Hz	~101.6 dB	0.92	Harmonic cluster, drifting mid-freq cluster	Main motor harmonic strong; mid-frequency drift suggests bearing stress
Drill	183 Hz + harmonics	~103.5 dB	0.87	Impact cluster at >2 kHz	Drilling cycles and transient events separated clearly
Packaging	500 Hz, 0.6 Hz pulses	~95 dB	0.79	Motor cluster; pulsed cutter cluster	Cutter cycle behavior visible; amplitude modulation indicates mechanical lag
Cigarette	48 Hz, ~150 Hz overlaps	~101.4 dB	0.88	Motor and roller clusters	Spectral overlap resolved; drift in roller cluster suggests tension changes
CNC Milling (Test)	2000 Hz broadband	~98 dB	0.83	High-frequency cluster indicative of bearing resonance	Potential early detection of bearing degradation

These results validate that advanced acoustic signal processing can dissect the complex mixture of machine noise into meaningful, interpretable components. The stability of autocorrelation peaks across machines reinforces that periodic mechanical behavior is well captured. Clustering effectively isolates fault-prone or variable clusters, enabling longitudinal tracking of changes (e.g. cluster drift, amplitude growth) as early warning indicators.

Comparisons across machines indicate that purely dominant frequencies do not tell the full story: clusters not dominant in dB can still carry critical diagnostic information (e.g., frequency drift, amplitude variability). In the lathe, although the 897 Hz cluster dominated, the emerging mid-frequency drift cluster may pre-empt mechanical wear. In the packaging machine, the cutter cluster's variability correlates with intermittent delays in bag cutting cycle—a practical performance issue.

These findings are consistent with literature trends emphasizing hybrid and model-based processing (Pan, 2025) and clustering under non-Gaussian noise (Drewnicka et al., 2025). Moreover, the identification of decaying cluster behaviours aligns with the physical modelling of faults as damped oscillations (Pichler et al., 2025). Thus, combining clustering and model-fitting enhances fault detection sensitivity in the face of industrial noise.

5. Conclusions and Recommendations

The outcomes of this study clearly demonstrate the potential and effectiveness of applying advanced acoustic signal processing techniques for the diagnosis, monitoring, and control of industrial machinery noise. By integrating accurate calibration, digital acquisition through Spectra LAB, and analytical post-processing in LabVIEW, the research established a coherent framework that translates complex acoustic signals into interpretable information about machine performance and health. The continuous and non-invasive nature of this approach represents a significant advantage compared to conventional diagnostic methods that rely on mechanical sensors or periodic inspections.

The results reveal that the use of Fast Fourier Transform (FFT) analysis, combined with power spectral density estimation and autocorrelation, allows the detection of both dominant harmonic sources and hidden transient events that are often masked within broadband industrial noise. The methodology proved especially valuable in identifying tonal components related to motor harmonics, as well as irregular frequency drifts indicative of gear wear or misalignment. The synchronized use of LabVIEW and Spectra LAB created a comprehensive diagnostic environment, where real-time monitoring was complemented by post-processing capabilities that enhanced precision and reduced measurement uncertainty.

The findings also emphasize the importance of calibration as the foundation of acoustic analysis. Without establishing a precise correlation between acoustic pressure and digital amplitude, spectral interpretations could be misleading. The careful calibration performed in this study ensured that frequency deviations remained within a minimal range, thereby increasing the reliability of subsequent analyses. Moreover, the integration of time–frequency clustering provided an additional layer of insight, allowing the separation of overlapping sources and improving the spatial–temporal resolution of the results.

From a practical standpoint, this methodology offers a valuable tool for predictive maintenance. The capacity to detect subtle changes in frequency stability, spectral amplitude, or autocorrelation strength provides early indicators of machine deterioration long before physical damage occurs. Continuous monitoring using such digital platforms could therefore replace the traditional reactive maintenance model with a proactive, condition-based approach. When implemented across multiple machines, these methods can form the backbone of an intelligent monitoring network that contributes directly to operational efficiency, reduced downtime, and improved workplace safety.

Furthermore, this research highlights the potential of integrating signal processing with artificial intelligence for automated interpretation. Machine learning algorithms can be trained using processed features—such as spectral peaks, autocorrelation coefficients, and cluster energy shares—to classify machine states or predict failure probabilities. Future work should focus on developing hybrid frameworks that combine physics-based acoustic models with data-driven classifiers. Such systems would not only enhance diagnostic accuracy but also provide adaptive capabilities that can learn from historical machine behavior.

In conclusion, the study underscores that acoustic signal processing is not merely an analytical tool but a strategic enabler of intelligent manufacturing. Through proper calibration, sophisticated digital analysis, and continuous feedback, acoustic signals can serve as reliable indicators of mechanical integrity and performance. The combined use of LabVIEW and Spectra LAB forms an accessible yet powerful foundation for implementing these techniques across diverse industrial environments. The continuing evolution of signal processing—augmented by advances in artificial intelligence, cloud connectivity, and edge computing—will undoubtedly strengthen its role as a cornerstone of predictive maintenance and industrial noise control in the coming decade.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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