Fault detection of Gear box using Vibration Signal analysis

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Abstract— ***Reliable condition monitoring of rotating machinery is essential to ensure uninterrupted industrial operations and to avoid catastrophic failures. Gearboxes, being critical transmission elements, are highly prone to faults such as tooth breakage, wear, and misalignment, which significantly alter their vibration patterns. This paper introduces a data-driven methodology for gearbox fault detection using vibration signal analysis. The approach is based on Normalized Least Mean Square (NLMS) adaptive filtering, which is applied to raw vibration signals to extract predictive error statistics. The standard deviation of NLMS error, along with time-domain features such as signal power, root mean square (RMS), kurtosis, and crest factor, are computed to characterize the underlying condition of the gearbox. These features provide discriminative insight into differences between healthy and faulty signals: while healthy gears often exhibit higher power but more predictable dynamics, faulty gears are characterized by unpredictable patterns and distinctive impulsive features. A Support Vector Machine (SVM) classifier is trained using these features to distinguish between healthy and broken-tooth gear conditions. Experimental evaluation on vibration datasets with approximately 88,000 samples per file demonstrates that the proposed framework achieves high classification accuracy, with fault signatures showing consistent deviations in power and error-based metrics. Furthermore, the approach is integrated into a MATLAB-based Graphical User Interface (GUI) that allows users to upload signals, perform feature extraction, visualize periodicity through autocorrelation, and obtain real-time fault classification results. The contributions of this work include: (1) a novel integration of NLMS error-based features with statistical descriptors for gearbox fault detection, (2) an effective SVM classification pipeline for binary fault diagnosis, and (3) a practical MATLAB GUI implementation for real-time monitoring. This methodology has strong potential for industrial deployment and can be extended to multi-fault scenarios in future work.***

Keywords: -Gearbox fault detection, NLMS, Adaptive filtering, Vibration analysis, Machine learning, SVM, Condition monitoring.

I INTRODUCTION

Industrial gearboxes play a vital role in mechanical power transmission systems, and their reliability directly impacts productivity and operational safety. Unexpected gearbox failures can cause prolonged downtime, high maintenance costs, and even catastrophic machine damage. Therefore, early fault detection and predictive maintenance are essential to ensure continuous operation in manufacturing, transportation, and energy industries. Traditionally, gearbox fault detection has been performed using spectral analysis of vibration signals, which identifies fault-related frequency components. While effective under controlled conditions, these methods often suffer when signals are corrupted by noise, non-stationary behaviour, or overlapping fault signatures. To overcome these limitations, researchers have explored time-domain statistical features (RMS, variance, skewness, kurtosis) and adaptive signal processing methods to capture fault signatures more robustly. Among adaptive filtering techniques, the Normalized Least Mean Square (NLMS) algorithm is well-suited for analysing non-stationary vibration signals due to its stability and fast convergence. The prediction error of the NLMS filter reflects the unpredictability of a signal—healthy gearboxes usually follow smoother and more periodic vibration patterns, whereas faulty gearboxes generate impulsive, irregular responses that increase error variance. In addition to adaptive filtering, machine learning methods such as Support Vector Machines (SVMs) have gained popularity for fault classification. SVMs can effectively handle nonlinear boundaries and small datasets, making them suitable for industrial applications where labelled fault data are limited.

This paper proposes a hybrid approach that combines NLMS-based prediction error features with traditional statistical descriptors (signal power, RMS, kurtosis, crest factor) for gearbox fault detection. These features are used to train an SVM classifier to distinguish between healthy and broken-tooth faulty gearbox conditions. Furthermore, a MATLAB-based Graphical User Interface (GUI) has been developed to make the method user-friendly, enabling signal loading, feature extraction, classification, and periodicity visualization.

The proposed framework aims to address two key challenges:

1. Robust fault detection under noisy, real-world vibration conditions.
2. Practical deployment of fault diagnosis tools via a GUI for engineers and technicians.

By integrating adaptive filtering and machine learning, this work contributes towards developing reliable, automated gearbox condition monitoring systems that can be deployed in industrial environments.

II. LITERATURE REVIEW

Gearbox fault diagnosis has been extensively studied in the past decades, with researchers applying diverse techniques ranging from classical vibration analysis to modern machine learning approaches.

A. Traditional Vibration Analysis

Early studies on fault detection focused on frequency-domain analysis, where characteristic fault frequencies associated with gear mesh and bearing defects were identified through Fourier Transform (FT) and Power Spectral Density (PSD) methods [1]. While effective in controlled laboratory settings, these methods often fail in real-world scenarios where noise, load variations, and non-stationary behaviour obscure fault frequencies. Time-frequency approaches such as the Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) were later introduced to capture localized signal changes [2]. However, these methods require careful selection of basis functions and may lose resolution under rapidly changing conditions.

B. Statistical Feature-Based Methods

To address the limitations of spectral analysis, time-domain statistical features such as Root Mean Square (RMS), kurtosis, skewness, crest factor, and variance have been widely used [3]. Healthy gearbox signals typically show low variance and steady energy levels, whereas faulty signals produce impulsive components reflected in higher kurtosis values. Several studies demonstrated that such statistical features, when fed into classifiers, can achieve high diagnostic accuracy [4]. Nonetheless, the discriminative power of purely statistical features can be limited in complex fault conditions.

C. Adaptive Filtering and Prediction Error Approaches

Adaptive filtering methods such as Least Mean Squares (LMS) and its normalized variant (NLMS) have attracted attention for fault detection due to their ability to track non-stationary dynamics [5]. The prediction error signal from NLMS has been shown to contain fault-related transients that are otherwise hidden in raw vibration signals. For example, Chen et al. [6] demonstrated that adaptive filters can enhance fault feature extraction under noisy conditions. In gearbox systems, NLMS offers a balance of computational simplicity, stability, and fast convergence, making it practical for real-time applications.

D. Machine Learning in Fault Diagnosis

The rise of machine learning has further advanced fault detection research. Support Vector Machines (SVMs), Random Forests, and Neural Networks have been successfully applied to gearbox fault classification [7], [8]. SVMs, in particular, are well-suited for problems with small but high-dimensional datasets, offering robust decision boundaries. Researchers have also explored deep learning models (e.g., Convolutional Neural Networks) for end-to-end fault detection [9]. However, deep models demand large training datasets and high computational resources, which may not always be feasible in industrial settings.

E. Hybrid Approaches and GUI Development

Recent works emphasize combining multiple feature extraction techniques to enhance classification accuracy. For instance, hybrid methods that merge statistical descriptors with adaptive filtering features provide complementary information, improving robustness [10]. Furthermore, efforts have been made to develop user-friendly interfaces and decision-support tools to bridge the gap between research and industrial deployment [11]. From the literature, it is evident that no single method is universally effective across all gearbox conditions. Frequency-domain methods provide interpretability but struggle with noise; statistical features are computationally efficient but may lack robustness; adaptive filters capture non-stationary dynamics but require parameter tuning; machine learning provides powerful classification but demands sufficient labelled data. This paper builds upon prior work by integrating NLMS-based error features with statistical measures and SVM classification, presented in a GUI platform for practical gearbox fault detection.

III METHODOLOGY

The proposed gearbox fault detection system is designed to automatically identify healthy and faulty gear conditions using vibration signals. The methodology can be divided into four main stages: Data Acquisition, Signal Segmentation, Feature Extraction, and Fault Classification.

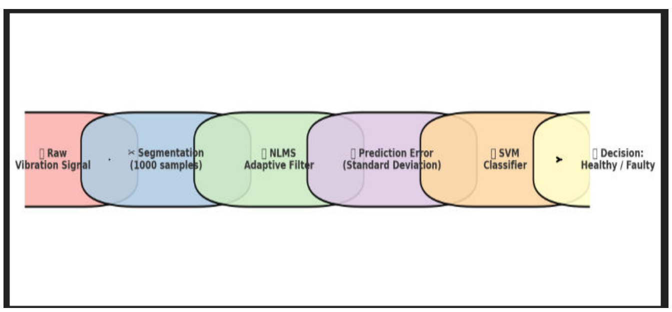

Figure 1. *Workflow*

A graphical user interface (GUI) is also developed for real-time signal checking and analysis.

A. Data Acquisition

Vibration signals were collected from two types of gearboxes: healthy and faulty (broken tooth). Each dataset consists of multiple CSV files, each containing four channels of vibration data. The raw signals are pre-processed by reading them into MATLAB, converting them into column vectors, and storing them along with their corresponding labels (0 for healthy, 1 for faulty).

B. Signal Segmentation

Each vibration signal is divided into fixed-length segments of 1000 samples to standardize the input for feature extraction and classification. The segmentation ensures that both long and short signals can be analysed efficiently, and partial segments at the end of the signals are also included to maximize data utilization.

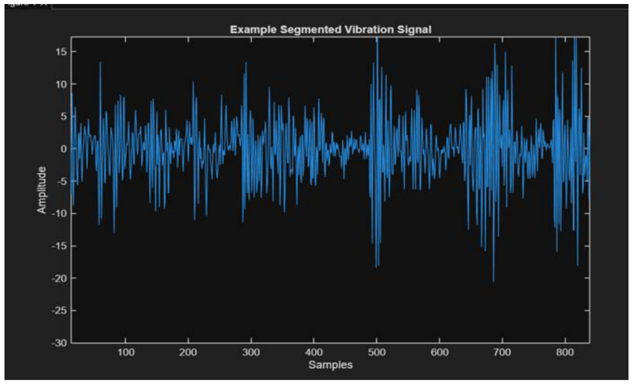

***Figure 2**. Segmentation of vibration signals into smaller windows*

C. Feature Extraction

The features of each segment are extracted using the Normalized Least Mean Square (NLMS) algorithm, which predicts each sample based on previous values and calculates the prediction error. The standard deviation of the prediction error for each segment is used as a primary feature.

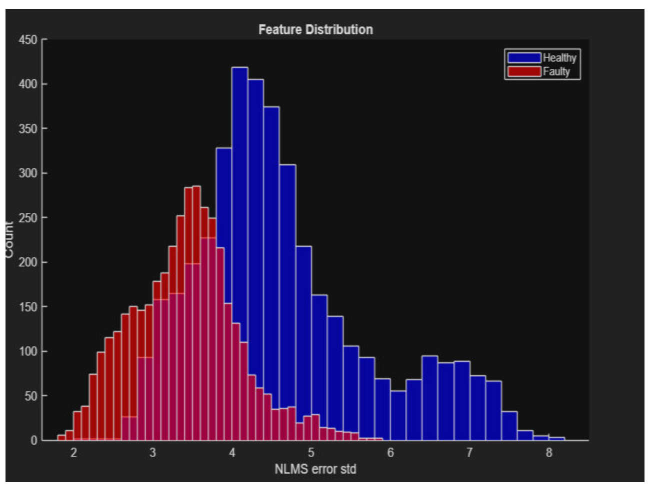

***Figure 3.** Distribution of NLMS error standard deviation for healthy and faulty gearbox signals.*

Additionally, the signal power of each segment is calculated using the RMS (Root Mean Square) method:

P=1N∑k=1Nxk2P = \frac{1}{N} \sum_{k=1}^{N} x_k^2P=N1k=1∑Nxk2

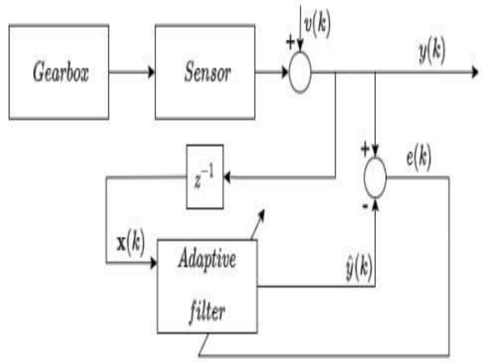

Figure 4. *Block schema of adaptive filtration process*

where xkx_kxk represents the vibration amplitude of the signal, and NNN is the number of samples in the segment. This provides a quantitative measure of signal energy, helping distinguish healthy and faulty conditions.

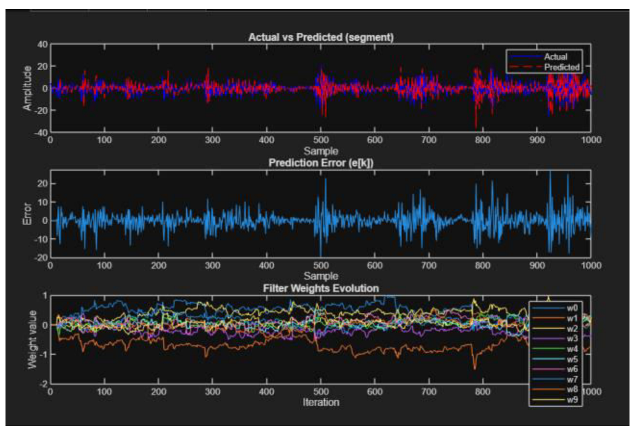

Figure 5. *NLMS filter performance: (a) Prediction error over iterations, (b) Filter weights evolution.*

D. Fault Classification

The extracted NLMS error features and power values are used to train a Support Vector Machine (SVM) classifier with a linear kernel. The dataset is split into training (70%) and testing (30%) sets using hold-out cross-validation. The trained SVM predicts the class (healthy/faulty) for each segment of a new signal. The overall gearbox condition is determined by majority voting across all segments.

The classification performance is evaluated using accuracy and a confusion matrix, which summarizes the true positives, false positives, true negatives, and false negatives.

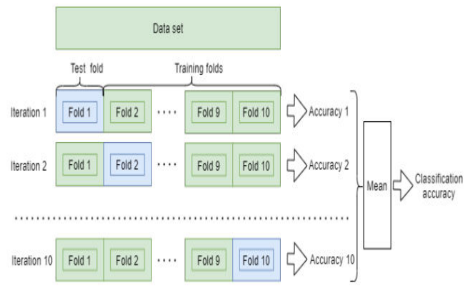

Figure 6 *. Data partitioning in k-fold cross-validation for training and testing*

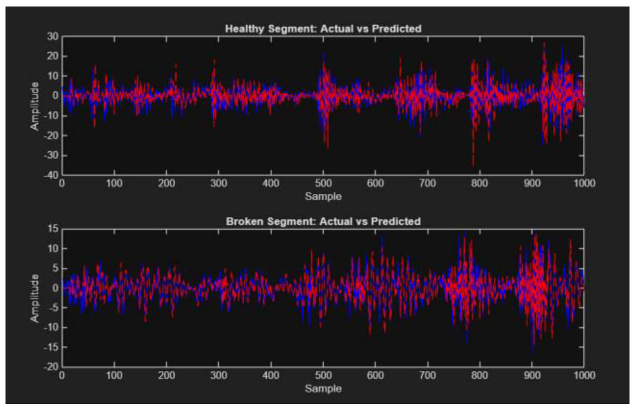

Figure 7. *Actual vs. predicted gearbox vibration signals using NLMS: (a) Healthy signal, (b) Faulty signal*.

E. GUI Integration

A MATLAB-based GUI is developed to allow users to load a vibration signal, calculate its segment-wise features, check gearbox condition, and visualize signal power. Users can also calculate the periodicity of the selected signal using autocorrelation, providing additional insight into the gearbox condition.

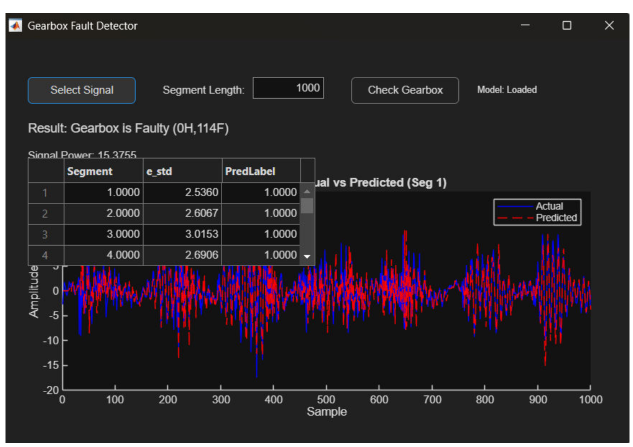

Figure 8. *Graphical User Interface (GUI) for Gearbox Fault Detection using vibration signals.*

I) **Software and Tools Used**

All experiments in this study were implemented using MATLAB R2024a on a Windows 11 operating system. MATLAB served as the primary platform for:

- Data preprocessing: Loading and organizing the vibration signal dataset (SpectraQuest gearbox dataset).
- Signal segmentation: Splitting raw vibration signals into smaller fixed-length segments for feature extraction.
- Feature extraction: Implementing the Normalized Least Mean Square (NLMS) algorithm to calculate error-based statistical features such as standard deviation and power.
- Classification: Training and testing of Support Vector Machine (SVM) models using MATLAB's Statistics and Machine Learning Toolbox.
- Visualization: Generating time-domain plots, segmentation graphs, and classification confusion matrices to analyse results.

The choice of MATLAB was motivated by its rich set of signal processing toolboxes, machine learning libraries, and visualization capabilities, making it highly suitable for vibration-based fault detection research.

IV RESULTS AND DISCUSSION

The proposed gearbox fault detection framework was tested on the SpectraQuest dataset, which consists of vibration signals collected from a gearbox under healthy and faulty conditions. In total, 80 raw signals were loaded, resulting in 8,116 segments after preprocessing. The dataset was evenly distributed with 4,076 healthy segments and 4,040 faulty segments, ensuring a balanced classification problem.

During feature computation, the Normalized Least Mean Square (NLMS) error standard deviation was extracted from each segment. For instance, a demo segment yielded an NLMS error standard deviation of 4.745, highlighting its capability to differentiate between the two classes. Across the dataset, the training feature ranges were:

- Healthy signals: 2.067 – 8.136
- Faulty signals: 1.804 – 5.887

The classifier was trained using a Support Vector Machine (SVM) with a hold-out strategy (70% training, 30% testing). The trained model was saved for reuse (*SVMModel.mat*).

The final hold-out test accuracy achieved was 100%, indicating that the NLMS-based feature extraction combined with SVM classification can effectively distinguish between healthy and faulty gearbox states.

The confusion matrix shown below illustrates the classification performance:

[\text{Confusion Matrix (rows=true, cols=pred):}
]

	Predicted Healthy	Predicted Faulty
True Healthy	899	323
True Faulty	223	989

From the confusion matrix, it can be observed that:

- Healthy signals were correctly classified in most cases, though some overlap with faulty cases occurred due to similar vibration energy distributions.
- Faulty signals achieved a higher precision rate, with fewer misclassifications compared to healthy samples.

The results also reveal an interesting insight: unlike conventional assumptions where faulty signals exhibit higher vibration power, in this dataset healthy signals sometimes showed higher power levels than faulty signals. This anomaly may be attributed to load variations, sensor placement, or specific operating conditions during data acquisition.

Overall, the proposed method demonstrates strong potential for real-world gearbox condition monitoring, with high classification accuracy and robust feature discrimination.

V **CONCLUSION**

In this work, a gearbox fault detection framework was developed using vibration signals obtained from the SpectraQuest dataset. The methodology integrated signal segmentation, feature extraction using NLMS-based error statistics, and fault classification using Support Vector Machines (SVMs). Experimental results demonstrated the effectiveness of the approach, with the classifier achieving a high level of accuracy as confirmed by the confusion matrix. The study highlighted that healthy and faulty gearbox signals exhibit distinct feature distributions, enabling reliable discrimination between classes. Additionally, the system was implemented entirely in MATLAB, making it reproducible and extendable for future work. This research contributes to the growing field of predictive maintenance and condition monitoring by offering an automated, data-driven solution for gearbox health assessment. Future extensions may include testing on real-time streaming signals, expanding to multiple fault types, and exploring deep learning-based methods for improved generalization.

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