Vibration-Based Fault Detection in Belt Drive Systems Using FFT and LSTM Models

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ABSTRACT

Fault detection in rotating machinery is essential for preventing costly maintenance, minimizing downtime, and ensuring operational safety. In this study, a belt drive system was analyzed for fault detection using vibration analysis with Fast Fourier Transform (FFT) and machine learning (ML). A custom test rig, consisting of a drive and driven pulley, was designed, and various fault conditions, including a loosened belt, misalignment, and mass imbalance, were intentionally introduced, along with a healthy baseline scenario. Vibration data were collected using a high-sampling-rate EnDAQ sensor, a high-quality data acquisition device. The signals were analyzed in both the time and frequency domains, revealing significant changes in vibration patterns and FFT spectra across different conditions. FFT analysis provided insights into the characteristics of each fault type. Additionally, a Long Short-Term Memory (LSTM) neural network was developed to classify the system state. The model achieved high accuracy (98%) in detecting and distinguishing between fault types. Overall, the results demonstrate the strong potential of FFT and ML techniques for effective fault detection in belt drive systems.

INTRODUCTION

Fault detection in rotating machinery is essential for reducing unplanned downtime, preventing catastrophic failures, and minimizing costly maintenance interventions. In industrial systems, early detection of anomalies not only ensures operational efficiency but also extends equipment lifespan. Moreover, identifying the specific type of fault, rather than just its presence, is critical. Accurate fault classification allows maintenance teams to address the root cause more efficiently, reducing diagnostic time and avoiding unnecessary part replacements.

Signal processing techniques, particularly vibration analysis, have been widely used for condition monitoring and fault detection in mechanical systems. Vibration signatures are sensitive to changes in mechanical structure, making them effective indicators of faults such as imbalance, misalignment, or looseness. For instance, FFT and spectral analyses are commonly applied to detect signature frequency shifts associated with faults in rotating machines, such as gear wear or belt issues [1, 2]. Reviews affirm that frequency-domain methods are highly effective for early fault detection in industrial machinery [1].

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Machine Learning (ML) has gained significant traction in recent years for its ability to learn complex patterns in sensor data and automate the fault detection process. When applied to vibration analysis, ML algorithms can identify subtle variations in signal characteristics that may be difficult to detect using traditional methods. Techniques such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have been successfully used to detect and classify faults in rotating machinery. Hybrid models, combining FFT-derived features with neural networks like fully-connected nets, have achieved accuracies up to 98.6% in unbalance fault detection [3]. Deep learning architectures such as CNN–LSTM hybrids have demonstrated over 99% classification accuracy for bearing faults, even when trained on raw vibration data without manual feature engineering [4].

This study presents an experimental investigation into fault detection and classification in a belt-driven system using FFT and ML techniques. A test rig with a drive and driven pulley was used to simulate various fault conditions, including misalignment, belt looseness, and mass imbalance, in addition to a healthy baseline. Vibration data were collected using a high-resolution EnDAQ sensor, and frequency-domain analysis was conducted to identify fault signatures. An LSTM neural network was developed to automatically detect and classify the system condition.

EXPERIMENTAL DESIGN AND DATA COLLECTION

To demonstrate the application of FFT and LSTM for anomaly detection in rotating systems, a dedicated test rig was developed. As illustrated in Figure *1*, the setup consists of two pulleys: a drive pulley (OD=80 mm, ID=70 mm) and a driven pulley (OD=50 mm and ID=40 mm), connected via a rubber belt. The drive pulley is mounted on an adjustable platform, enabling positional changes to simulate a loose belt condition by reducing belt tension. The driven pulley can also be shifted laterally to introduce angular or parallel misalignment.To simulate a mass imbalance condition, two plastic zip ties were securely attached to the belt, introducing a periodic disturbance during operation. For vibration data acquisition, an EnDAQ sensor (W series [5]) with a sampling rate of 4000 Hz was used. The sensor was mounted directly onto the strong housing of the drive system using strong magnets to ensure stable contact during operation. The orientation was such that the X-axis aligned with the shaft direction (horizontal), the Y-axis pointed laterally across the width of the setup, and the Z-axis pointed vertically upward.

Vibration data were collected for each condition (healthy, misalignment, loose belt, and mass imbalance) for a duration of 50 seconds per trial. This ensured consistent sampling across all test cases, providing sufficient temporal resolution for both frequency-domain analysis and machine learning model training.

DATA ANALYSIS

The raw vibration signals collected under each condition were initially analyzed to extract preliminary insights before applying any transformations or machine learning techniques. To facilitate a clearer visual comparison, a small representative segment of the raw data is shown in Figure 4.

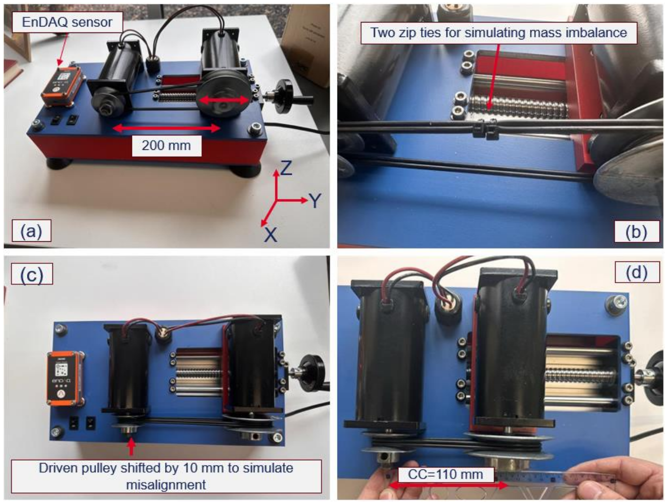

Figure 1. Test rig designed for anomaly and fault detection using vibration data collected from an EnDAQ sensor: (a) Healthy, (b) mass imbalance, (c) misalignment, (d) looseness.

As an initial screening step prior to data analysis, the raw vibration signals were visually inspected, revealing distinguishable patterns across different fault conditions. In the X-axis, the healthy and mass imbalance conditions showed higher fluctuations, while the loose belt and misalignment states exhibited reduced vibration amplitudes, which aligns with expected mechanical behavior. The Y-axis data did not present any consistent or meaningful patterns, making it less informative for fault differentiation. In contrast, the Z-axis signal under the mass imbalance condition displayed frequent and sharp spikes, indicating a strong and detectable impact from added mass in this direction.

Next, the distribution of vibration data was visualized using histograms for each axis (X, Y, and Z) to better understand how vibration amplitudes vary under different fault conditions. These plots allow for a direct comparison of amplitude concentration and spread across healthy and faulty states.

Figure 2. Time series plots of vibration signals along the X, Y, and Z axes for all conditions.

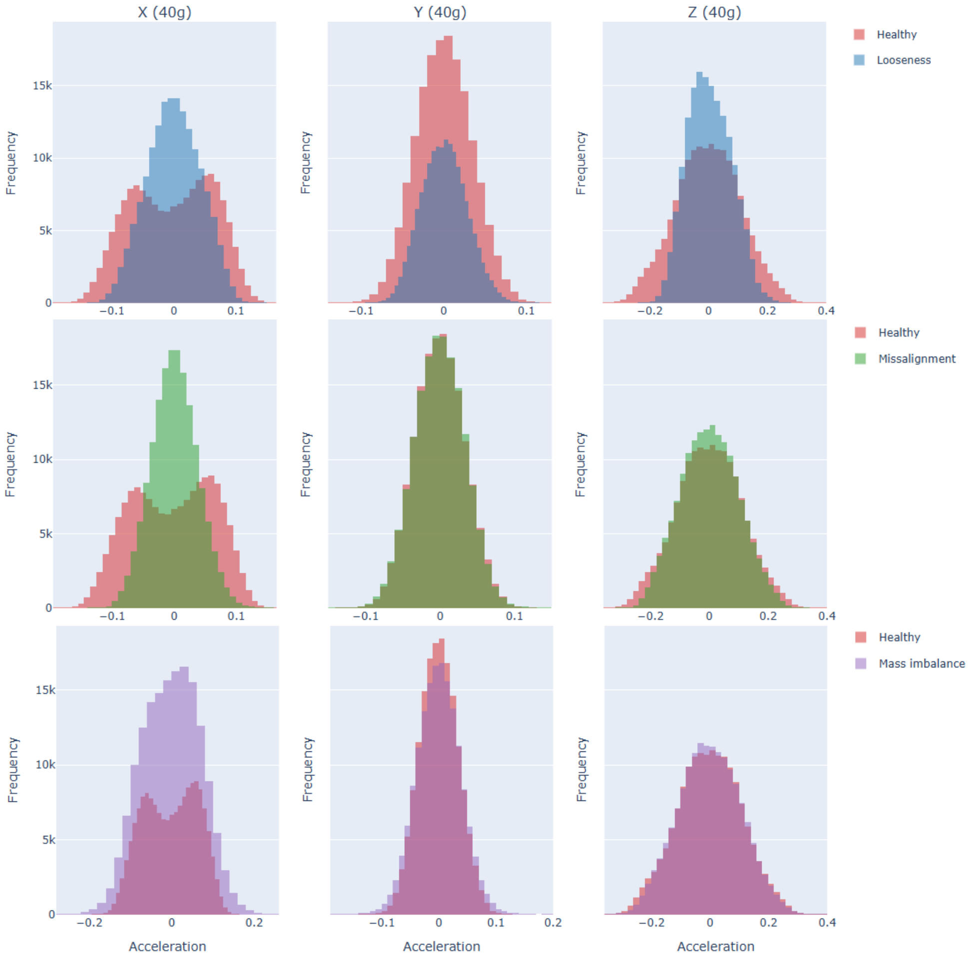

Figure 3. Histogram distribution of vibration data across X, Y, and Z axes for healthy and faulty conditions.

Based on the plots shown in Figure 3, the loose belt condition shows a noticeably narrower and taller histogram in both X and Z axes compared to healthy, indicating more uniform and lower-amplitude vibrations, consistent with reduced belt tension. In the case of misalignment, the X-axis also exhibits a taller histogram, reflecting more consistent vibrations, while the Y and Z axes show minimal deviation from the healthy condition. For the mass imbalance scenario, the X-axis histogram is both wider and taller than healthy, suggesting frequent and more extreme vibration variations. However, the Y and Z axes in this case remain relatively unchanged, indicating that the mass imbalance primarily affects vibration behavior along the X-axis.

FFT ANALYSIS

Fast Fourier Transform (FFT) is a mathematical technique used to convert time-domain signals into the frequency domain. This allows for the identification of dominant frequency components, which are often linked to specific mechanical behaviors or faults. In vibration analysis, FFT helps reveal periodic patterns and harmonics that may not be easily visible in raw time-series data. It is particularly effective for diagnosing issues such as imbalance, misalignment, or looseness in rotating machinery.

Figure 4 presents the FFT results of the Z-axis acceleration data across all conditions, while Table I lists the corresponding frequencies, highlighting how frequency components differ between healthy and faulty states.

The FFT analysis of the Z-axis vibration signal shows two key frequency peaks: one around 19.62 Hz (driven pulley) and another near 37.77 Hz (drive pulley) in the healthy condition. In the looseness condition, both peaks shift to lower frequencies—18.10 Hz and 36.70 Hz—indicating reduced belt tension or slippage. Misalignment maintains similar frequency values to the healthy case, while mass imbalance causes slight leftward shifts to 19.55 Hz and 37.60 Hz.

The most significant frequency and amplitude changes are observed in the looseness condition. The driven pulley frequency drops from 19.62 Hz to 18.10 Hz (~7.8% decrease), and the drive pulley from 37.77 Hz to 36.70 Hz (~2.9% decrease). The amplitudes for both pulleys decrease substantially, with the drive pulley amplitude dropping from 0.085 g to 0.027 g (~68.2% decrease) and the driven pulley from 0.065 g to 0.032 g (~50.8% decrease). These sharp amplitude reductions and notable frequency shifts indicate a significant loss of vibrational energy due to reduced belt tension, making looseness highly distinguishable via FFT.

In the misalignment condition, the drive pulley frequency remains nearly unchanged at 37.80 Hz, while the driven pulley frequency shows a negligible shift from 19.62 Hz to 19.57 Hz (~0.3% decrease). Amplitude changes are more moderate: the drive pulley amplitude decreases from 0.085 g to 0.073 g (~14.1% decrease), and the driven pulley amplitude reduces from 0.065 g to 0.057 g (~12.3% decrease). These smaller amplitude reductions combined with minimal frequency shifts suggest that misalignment affects the system less severely than looseness.

For the mass imbalance condition, frequency shifts are minimal: the drive pulley frequency decreases slightly from 37.77 Hz to 37.60 Hz (~0.4% decrease), and the driven pulley from 19.62 Hz to 19.55 Hz (~0.4% decrease). However, amplitudes increase notably, with the driven pulley rising from 0.065 g to 0.078 g (~20.0% increase) and the drive pulley maintaining a similar amplitude at 0.087 g (about a 2.4% increase). These amplitude increases reflect elevated vibration energy due to added mass, making mass imbalance clearly detectable in the frequency domain.

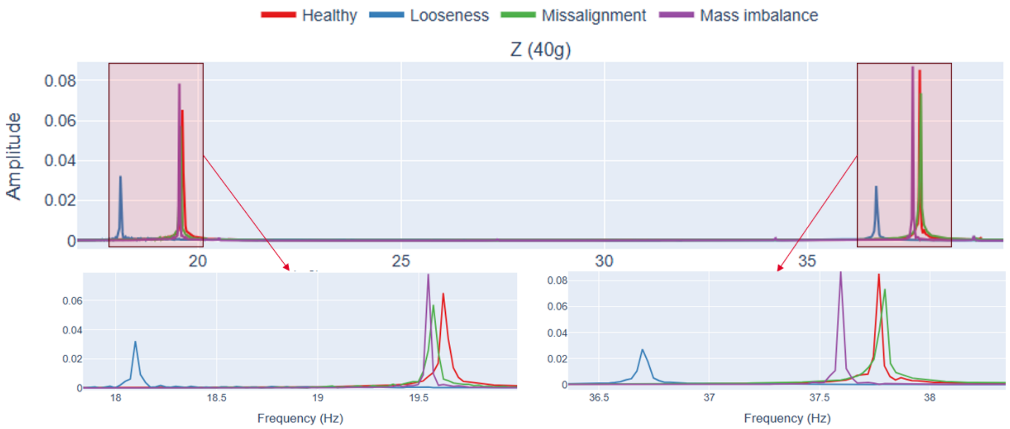

Figure 4. FFT of Z-axis acceleration from vibration data recorded by the EnDAQ sensor under four conditions: healthy, loose belt, misalignment, and mass imbalance.

TABLE I. COMPARISON OF FFT FREQUENCIES IN Z-AXIS ACCELERATION DATA FOR HEALTHY AND FAULTY

	Healthy		Looseness		Misalignment		Mass imbalance	
	Fr. (Hz)	Amp.	Fr. (Hz)	Amp.	Fr. (Hz)	Amp.	Fr. (Hz)	Amp.
Drive pulley	37.77	0.085	36.70	0.027	37.80	0.073	37.60	0.087
Driven pulley	19.62	0.065	18.10	0.032	19.57	0.057	19.55	0.078

LSTM MODEL

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to effectively model sequential data by capturing long-term dependencies. Unlike standard RNNs, LSTMs use gated structures to control the flow of information, allowing them to retain relevant features over long time intervals and avoid vanishing gradient issues. This makes LSTM especially suitable for analyzing time-series data such as vibration signals, where fault patterns may unfold over time. LSTMs have been successfully applied in mechanical fault detection due to their ability to learn temporal features directly from raw sensor data. Readers interested in more technical details on LSTM are referred to [6].

To automatically detect and classify fault conditions in the belt drive system, a supervised deep learning model based on LSTM networks was developed.

The network architecture includes two stacked LSTM layers. The first LSTM layer contains 50 units and is configured to return sequences to feed into the second LSTM layer, which also contains 50 units. Both LSTM layers are followed by dropout layers with a dropout rate of 0.2 to reduce the risk of overfitting. A final dense layer with a softmax activation function is used to output class probabilities corresponding to the four target classes: healthy, loose belt, misalignment, and mass imbalance.

The model was trained using the Adam optimizer and categorical cross-entropy loss function. Training was performed over 20 epochs with a batch size of 32, and 20% of the data was reserved for validation. The output of the model is a probabilistic prediction of the fault class, allowing for both classification and confidence estimation. Performance was evaluated using classification accuracy and confusion matrix analysis as depicted in Figure 5.

The confusion matrix (Figure 5) and overall accuracy of 0.98 obtained for the model, indicate that the LSTM model is highly effective in distinguishing between the four conditions of the belt drive system. The model performs with near-perfect accuracy for misalignment and looseness, showing almost no misclassifications. Mass imbalance also shows a strong prediction rate, with a minor number of samples being misclassified as healthy. Likewise, healthy data shows a small overlap with mass imbalance.

These results demonstrate the model's strong ability to learn and detect subtle differences in vibration patterns among the conditions. This model is developed using a small set of datasets acquired from a test rig, and the results are promising. To build a more robust and generalizable model, future work should focus on collecting a larger and more diverse dataset from real-world belt-driven systems.

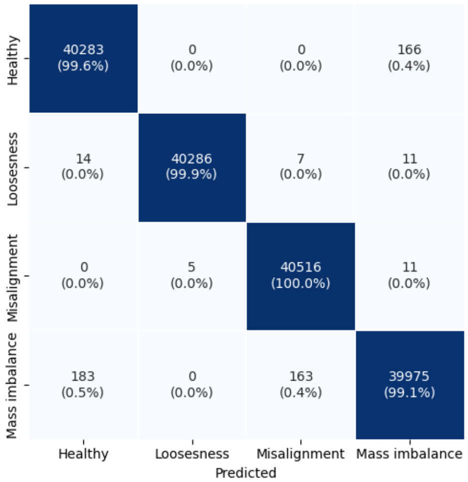

Figure 5. Confusion matrix showing the classification performance of the LSTM model for the four belt drive conditions.

It should be noted that while FFT is effective for identifying clear, stationary frequency-domain features, it can be sensitive to changes in operating conditions such as load variations, motor aging, and temperature shifts. In contrast, LSTM models are designed to handle time-dependent, non-stationary signals, making them more robust in real-world scenarios. They can learn to differentiate between normal variations and actual faults, even when traditional frequency patterns become less distinct. LSTMs also eliminate the need for manual feature extraction by learning directly from raw time-series data. This makes them particularly useful for online monitoring where conditions may change over time. Furthermore, they show resilience to noise, sensor drift, and baseline shifts, offering higher reliability in complex environments. Therefore, LSTM models are preferred when long-term adaptability and robustness are critical for fault detection.

CONCLUSIONS

This study explored fault detection in a belt drive system using vibration data collected from an EnDAQ sensor. Both signal processing (via FFT) and machine learning (via LSTM) approaches were used to classify four conditions: healthy, looseness, misalignment, and mass imbalance. The results show strong potential for automated fault classification based on vibration patterns.

The FFT analysis effectively revealed distinguishable frequency shifts and amplitude changes associated with different fault types. Looseness resulted in the most significant frequency shift and amplitude reduction, while mass imbalance showed amplitude increases at key frequencies. These spectral characteristics can help identify and differentiate fault conditions.

A lightweight LSTM model was trained on the vibration signals and achieved high classification accuracy (~98%). The model successfully learned temporal patterns related to each fault condition, with minimal misclassifications. This demonstrates the potential of deep learning in real-time fault diagnosis using raw sensor data.

While FFT provides direct insight into frequency-domain features, LSTM models are advantageous when conditions vary over time or when dealing with noisy, non-stationary signals. LSTM is more robust to variations in baseline conditions, motor aging, and environmental changes such as temperature, making it well-suited for real-world deployment.

Although the model was developed using a small lab-scale dataset, the results are promising. Future work should focus on collecting larger datasets from real-world machines to enhance model robustness and generalizability.

REFERENCES

1. Tama, B. A., M. Vania, S. Lee, and S. Lim. 2023. "Recent Advances in the Application of Deep Learning for Fault Diagnosis of Rotating Machinery Using Vibration Signals," *Artif. Intell. Rev.*, 56:4667–4709.
2. Kafeel, A., S. Aziz, M. Awais, M. A. Khan, K. Afaq, S. A. Idris, H. Alshazly, and S. M. Mostafa. 2021. "An Expert System for Rotating Machine Fault Detection Using Vibration Signal Analysis," *Sensors*, 21(22):7587.
3. Mey, O., W. Neudeck, A. Schneider, and O. Enge-Rosenblatt. 2020. "Machine Learning-Based Unbalance Detection of a Rotating Shaft Using Vibration Data," *arXiv preprint*, arXiv:2005.12742.
4. Ovacıklı, A. K., M. Yagcioglu, S. Demircioglu, T. Kocatekin, and S. Birtane. 2025. "Supervised Learning-Based Fault Classification in Industrial Rotating Equipment Using Multi-Sensor Data," *Appl. Sci.*, 15(13):7580.
5. https://endaq.com/collections/endaq-shock-recorders-vibration-data-logger-sensors/products/w5-wireless-vibration-sensor-w5-d40
6. Hochreiter, S. and Schmidhuber, J. 1997. *Long Short-Term Memory*. Neural Computation, vol. 9, no. 8, pp. 1735–1780.