Feature Extraction for Vibration Analysis Using Machine Learning

Objective:

Extract meaningful features from vibration data to classify different types of mechanical issues (e.g., imbalance, misalignment, bearing damage) in an electric motor using accelerometer readings along the X, Y, and Z axes.

Instructions:

1. Data Preprocessing:

- Load the time-series accelerometer data (X, Y, Z axes).
- Visualize the raw time-domain signals for each axis. Ensure that the data is properly sampled and free from noise or missing values.

2. Time-Domain Features:

- Compute basic statistical features for each axis, such as mean, standard deviation, variance, max/min values, peak-to-peak amplitude, and RMS (Root Mean Square).
- Comment on how these features reflect the overall vibration levels.

3. Frequency-Domain Features:

- Apply a Fourier Transform (FFT) to convert the vibration signals into the frequency domain.
- Identify dominant frequencies and extract features such as the peak frequency, total power, and power in specific frequency bands.
- Discuss how these frequency features might relate to potential mechanical issues such as imbalance or resonance.

4. Advanced Features: (if required)

- Calculate advanced statistical features such as skewness, kurtosis, and the envelope of the vibration signals using the Hilbert Transform.
- Perform a Wavelet Transform on the signal and extract time-frequency domain features.

5. Feature Combination:

- Combine time-domain and frequency-domain features into a single feature set.
- Visualize the extracted features using plots or pairwise scatter plots to examine their relationships.

6. Discussion:

- Based on the extracted features, discuss which features you think will be the most useful for classifying mechanical issues like imbalance, and explain why.

Classical Statistical Methods for Vibration Analysis

Objective:

Use classical statistical methods to analyze vibration data and identify potential anomalies or mechanical faults in an electric motor. The goal is to detect issues such as imbalance, misalignment and in particular bearing damage by applying statistical tests and signal analysis.

Instructions:

1. Fourier Analysis:

- Perform a Fourier analysis (FFT) on the vibration signals. Identify any dominant frequencies that could indicate mechanical issues such as imbalance, bearing damage or imbalance.

- Plot the frequency spectrum for each axis and highlight the frequencies of interest.

2. Statistical Process Control (SPC):

- Implement control charts (e.g., Shewhart or EWMA) for the vibration data. Use the mean and variance of the signal to detect any significant deviations from normal operation.

- Explain any observed trends or out-of-control signals w.r.t. potential mechanical failures.

3. Time-Series Analysis:

- Fit an autoregressive (AR) model to the time-series data to capture patterns in the vibrations.

- Use this model to predict future data points and compare them to actual observations. Discuss any anomalies or deviations that may indicate a fault.

4. Envelope Analysis:

- Use the Hilbert Transform to calculate the envelope of the signal. Analyze the amplitude of the envelope and identify any patterns that could indicate transient events like impacts or faulty bearings.

- Plot and interpret the envelope for each axis, commenting on any unexpected behavior.

5. Hypothesis Testing:

- Conduct a hypothesis test (e.g., t-test or chi-square test) to compare the vibration data from a balanced motor versus an unbalanced motor. Determine if the difference in vibration patterns is statistically significant.

- Clearly state your null hypothesis and alternative, and present the results of the test.

6. Resonance and Frequency Analysis:

- Identify the natural frequencies of the system by analyzing the vibration data. Use a Bode plot to visualize the amplitude and phase response of the motor system over a range of frequencies.

- Discuss how resonance might affect motor performance and what you observe from the plot.

7. Discussion:

- Summarize your findings from the statistical methods you applied. What potential mechanical issues do the data suggest? How do the classical statistical methods compare to machine learning-based approaches for this type of analysis?

Additional Feature Extraction Techniques (for Machine Learning)

1. Principal Component Analysis (PCA):

- **Objective:** Reduce the dimensionality of the vibration data while preserving the most important information.

- **Task:** Apply PCA on the extracted features (from time and frequency domains) to identify which combinations of features explain the most variance. This can help students reduce feature redundancy and identify which features are most critical for classification.

2. Autocorrelation Features:

- **Objective:** Analyze the autocorrelation of the vibration signal to detect periodicity or recurring patterns over time.

- **Task:** Compute the autocorrelation function for each axis and use it to extract features like lag-time peaks, which may indicate repetitive faults such as imbalance, misalignment or bearing damage.

3. Signal Energy and Entropy:

- **Objective:** Measure the complexity and energy distribution within the vibration signal.

- **Task:** Calculate signal energy and entropy to quantify the regularity or unpredictability in the motor's vibrations. High entropy might indicate erratic or complex vibration patterns, suggesting a mechanical issue.

4. Cepstral Analysis:

- **Objective:** Perform cepstral analysis to detect periodic echoes in the frequency domain, often associated with repetitive mechanical impacts.

- **Task:** Apply a cepstral transform on the vibration data to extract quefrency domain features, which can help identify cyclical faults in bearings.

5. Cross-Correlation Between Axes:

- **Objective:** Investigate the relationships between different axes of vibration (X, Y, Z) to detect coupled or multi-axis faults.

- **Task:** Compute the cross-correlation between pairs of axes to examine if vibrations in one axis are influencing others. This can be indicative of complex faults such as misalignment, imbalance or bearing damages across multiple dimensions.

Additional Classical Statistical Methods

1. Multivariate Analysis (Hotelling's T^2):

- **Objective:** Extend traditional statistical tests to handle the multivariate nature of vibration data.

- **Task:** Apply Hotelling's T^2 test to assess whether the mean vector of the vibration data (X, Y, Z axes combined) significantly deviates from a baseline or expected normal operating state.

2. Cross-Spectral Density (CSD):

- **Objective:** Analyze the frequency domain relationship between different axes.

- **Task:** Use cross-spectral density analysis to study how energy is distributed across frequencies between two signals (e.g., X and Y axes). This can help identify shared mechanical sources of vibration.

3. Cumulative Sum (CUSUM) Control Charts:

- **Objective**: Detect small shifts in vibration signals over time.

- **Task**: Implement CUSUM charts to identify gradual drifts or subtle shifts in vibration levels that could indicate early-stage mechanical issues.

4. Bootstrap Hypothesis Testing:

- **Objective**: Use resampling techniques to test the significance of differences between different vibration states (e.g., balanced vs. unbalanced motor).

- **Task**: Perform bootstrap resampling on vibration data to generate empirical distributions and test hypotheses about the mean or variance of the signals.

5. Spectral Kurtosis (SK):

- **Objective**: Use spectral kurtosis to detect transients in vibration signals that are localized in both time and frequency.

- **Task**: Apply spectral kurtosis analysis to identify non-stationary vibration events such as impacts or faults that are hidden within the vibration noise.

6. Stochastic Process Models

- **Objective**: Model the vibration signal as a stochastic process to understand its underlying structure.

- **Task**: Fit models such as Markov chains or Poisson processes to the vibration data to describe the probability of transitions between states (normal, faulty) based on past observations.

Practical Extensions for Both Machine Learning and Classical Approaches

1. Real-Time Monitoring and Feature Streaming:

- **Objective:** Develop a system that can process vibration data in real-time and continuously update feature calculations or statistical control charts.

- **Task:** Set up a system that processes streaming accelerometer data and dynamically updates feature calculations (e.g., RMS, kurtosis, peak frequencies) or control chart thresholds, providing real-time feedback on potential motor issues.

2. Fault Classification:

- **Objective:** Combine multiple statistical methods and machine learning features to create a classification model that predicts different types of faults (e.g., imbalance, misalignment, bearing damage).

- **Task:** After feature extraction and statistical analysis, build a classification model (even with classical methods like Linear Discriminant Analysis (LDA) or Quadratic Discriminant Analysis (QDA)) that can label different mechanical faults based on the extracted characteristics.

3. Sensitivity Analysis:

- **Objective:** Evaluate how sensitive the extracted features or statistical metrics are to different fault types or vibration levels.

- **Task:** Perform a sensitivity analysis on the features or statistical methods, varying the parameters of the system (e.g., speed, load) and observing how different metrics change.