The University of Texas Rio Grande Valley
Center for Multidisciplinary Research Excellence in Cyber-Physical Infrastructure Systems (MECIS)

Feature Extraction from Vibration Signatures Acquired from Railroad Bearing Onboard Condition Monitoring Sensors

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Abstract

The railway industry experiences over 1,000 train derailments annually. This project strives to develop AI/ML algorithms to extract train speed from the vibration signatures collected by the University Transportation Center for Railway Safety (UTCRS) wireless onboard sensors. Train speed is a required input for the developed algorithm that will assess bearing health through three-levels of analysis. Models such as linear regression, support vectors, and random forest regression are tested and their performance is evaluated using mean absolute error and mean squared error.

Introduction & Background

- The UTCRS utilizes its railroad bearing testers to perform laboratory experiments and collect vibration, temperature, and load data at various operating speeds.
- Continuous vibration signatures from test bearings are acquired by the onboard sensors every 10 minutes at a sampling frequency of 5120 Hz for 16 seconds.
- Although there is a complex relationship between speed and vibrations, it can be captured using machine learning techniques.
- Regression machine learning models are typically used to predict continuous outputs; therefore, this type of models is best suited for this task.

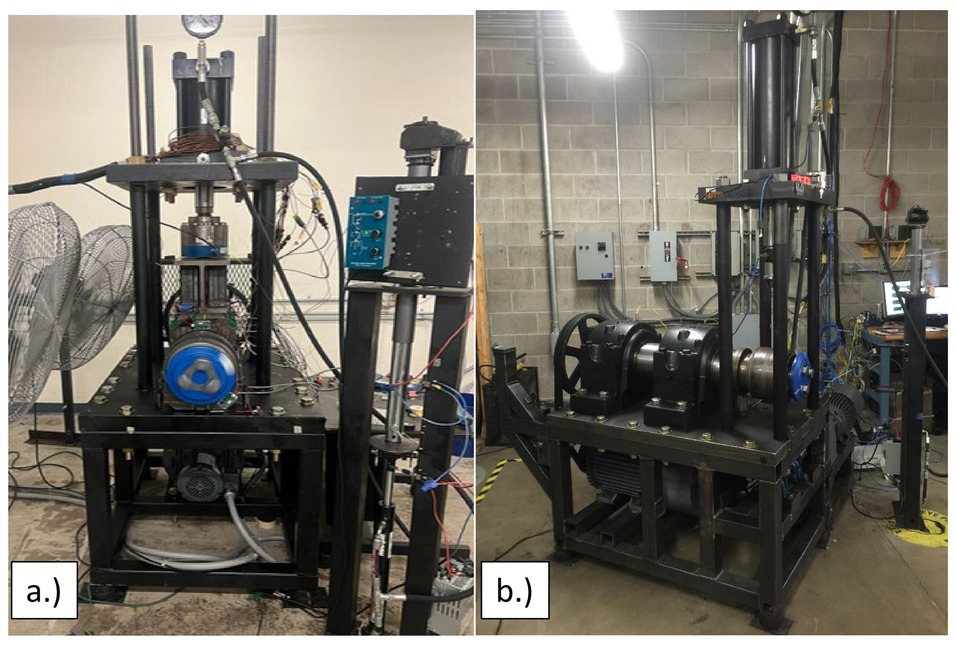

*Figure 1: **a.)** Four Bearing Tester (OB4T) **b.)** Single Bearing Tester (SBT)*

- Converting data to the frequency-domain spectrum will highlight critical vibrational information not typically captured by the time-domain data, later shown in figure 4.

$$\omega_o = \omega_{cone} \qquad \omega_{cage} = \left(\frac{R_{cone}}{R_{cone} + R_{cup}}\right)\omega_{cone}$$

$$\omega_{roller} = \left(\frac{R_{cone}}{D_{roller}}\right)\omega_{cone} \qquad \omega_{out} = 23\omega_{cage}$$

$$\omega_{in} = 23\,(\omega_{cone} - \omega_{cage}) \qquad \omega_{rollerdef} = \left(\frac{R_{cup}}{R_{roller}}\right)\omega_{cage}$$

Figure 2: Critical Frequency Equations

Methodology

- Extensive vibration data is gathered from operational bearings equipped with the UTCRS onboard monitoring system.
- Data is preprocessed for experimentation utilizing MATLAB.
  1. Time-domain to frequency-domain conversion.
  2. Critical frequency analysis using envelope analysis.
  3. Noise reduction.
  4. Normalization of datasets.
- Regression supervised learning.

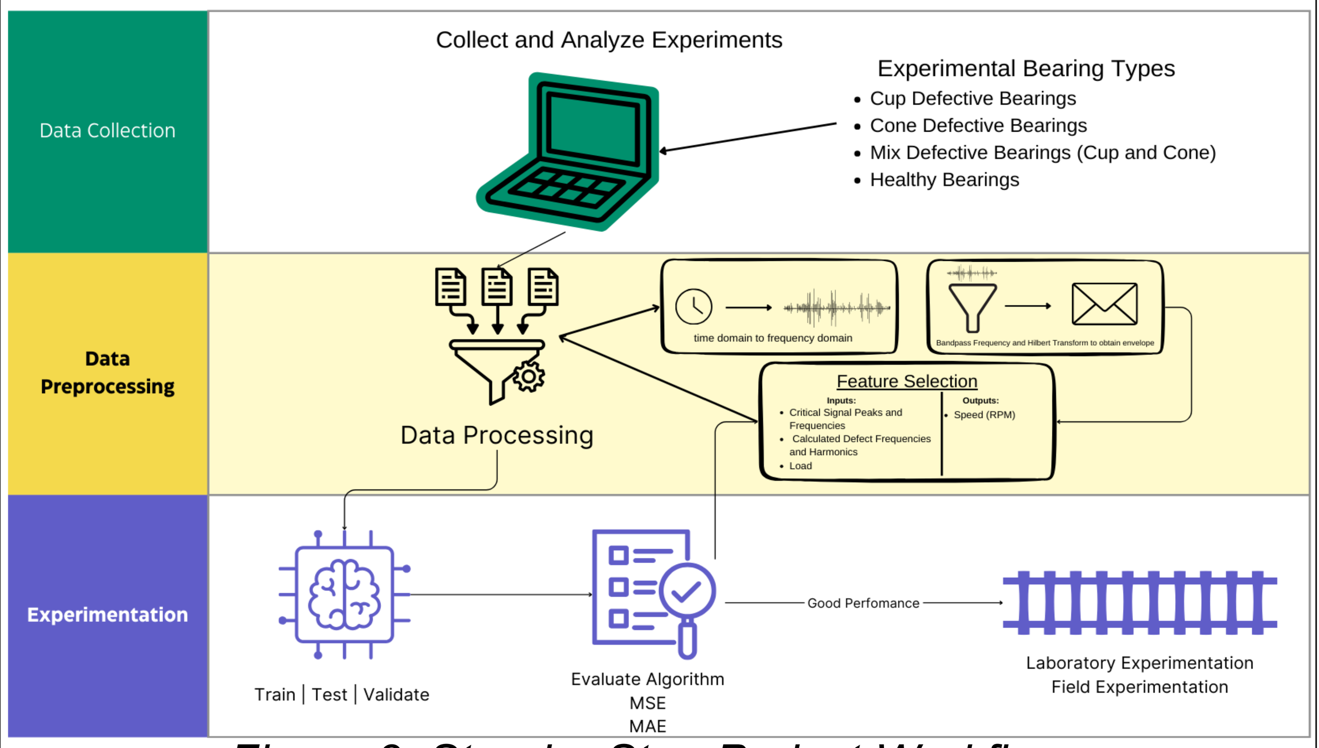

Figure 3: Step-by-Step Project Workflow

Data and Results

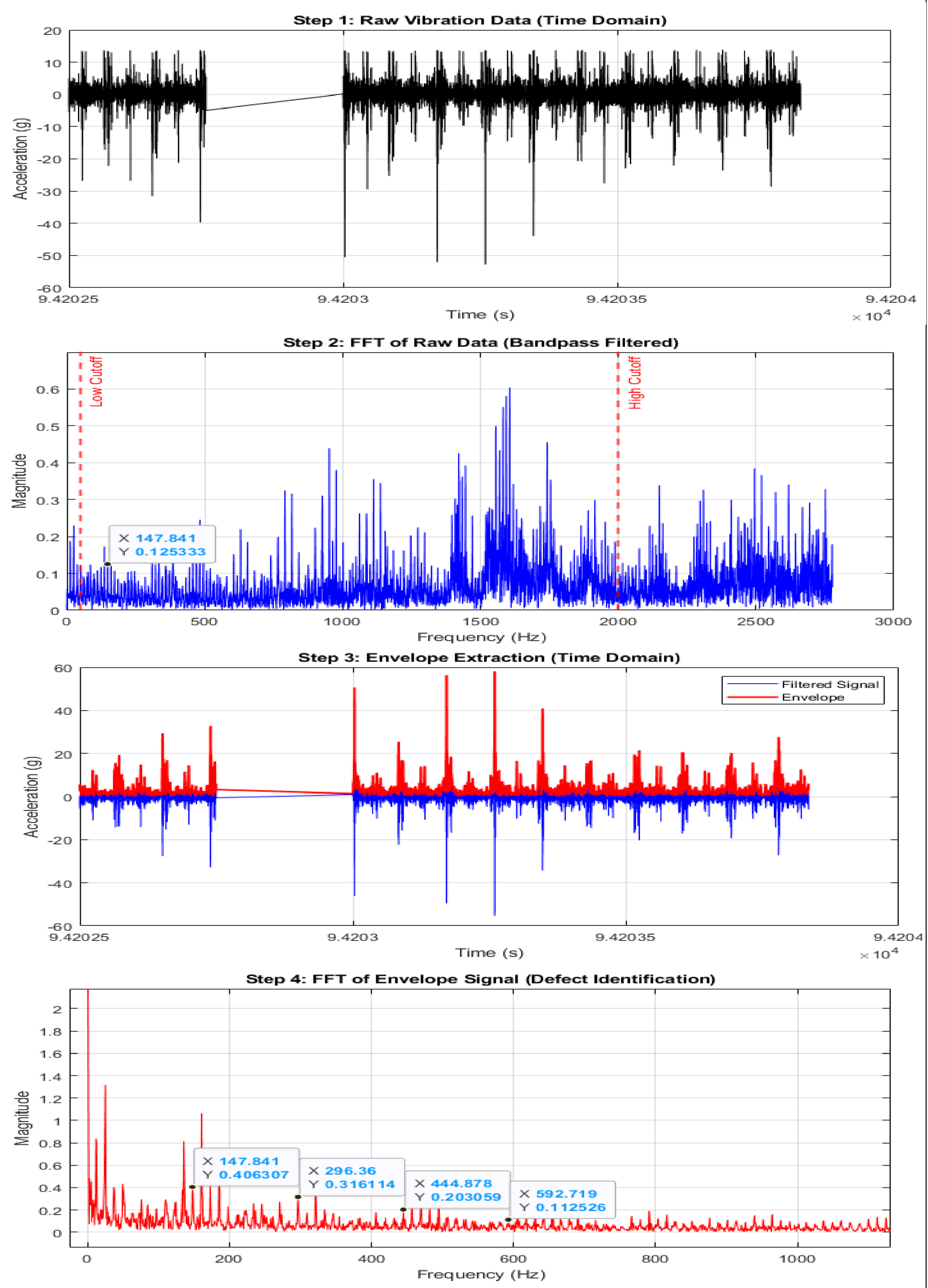

Figure 4: Data preprocessing steps in determining defect frequencies

- After collecting relevant data, it is input into a pipeline of several algorithms to evaluate model performance.

Algorithm Performance			
Metrics	Linear Regression	Random Forest Regression	Support Vector Regression
Mean Squared Error	1.7	5	431.4
Mean Absolute Error	1	1.4	16.5

Table 1: Algorithm Performance without Hyperparameter Tuning

- Table 1 demonstrates better performance of Linear Regression, indicating a significant linear relationship between the features speed, load, and frequency.

Conclusions & Future Work

- The ability of the model to accurately predict speed from the acquired vibration signatures will allow for real-time assessment of bearing condition.
- Real-time prediction affords rail operators the opportunity to schedule proactive maintenance, thus avoiding costly and unnecessary train stoppages and delays on main lines.
- The developed AI/ML models will be integrated into the onboard monitoring system's existing software, followed by extensive field testing to assess real-time performance and reliability.
- Combination of models is a possibility to further improve prediction accuracy.

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