Predicting Cycling Drivetrain Efficiency from Sound using an Auto-Encoder

Excitement – Integrity

Machine Learning – Auto-Encoder – Audio Classification

Spring 2024

PURDUE UNIVERSITY

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Abstract

In the past decade, the cycling industry has seen significant technological advancements aimed at improving both bicycle and rider performance. One area that has received little attention is the development of chain lubricants. Recent studies have demonstrated the effectiveness of machine learning models for use in machine tool predictive maintenance and replacement using analysis of audio data. A comprehensive study was conducted to facilitate a better understanding of the relationship between a chain's efficiency and its audio characteristics. By modifying an existing chain testing rig with audio gathering equipment, over 300GB of audio data was collected. An autoencoder machine learning model was trained to analyze the Mel-Frequency Cepstral Coefficients (MFCCs) of the collected data. An autoencoder, while unable to predict time since lubrication or chain efficiency, was shown to accurately determine the presence of a bicycle chain when given audio data. To improve the robustness of the model, a supervised machine learning model, such as a Recurrent Neural Network, was proposed. The predictive nature may prove useful in re-lubricating chains at more efficient time intervals.

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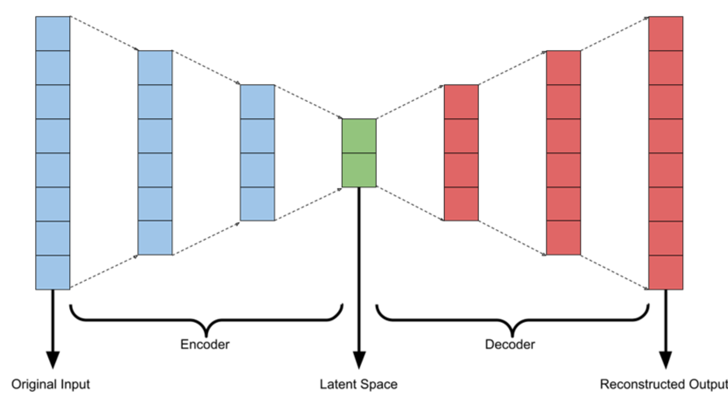
Project Overview

Many cyclists are familiar with the squeaky sounds emitted from a chain as the lubricant wears off. It can be difficult to determine when to optimally apply new lubricant. This project aims to tackle that problem by using machine learning to determine when to apply lubricant based on the chain's audio. This model may also be able to determine the efficiency of the chain, as data suggests there may be a correlation. An auto-encoder was proposed as the machine learning model. The initial approach involved feeding the model specific training data so that there was a relationship between the magnitude of the reconstruction error and some other metric. Initial false positives appeared to show this method effective, however this initial methodology contained many flaws due to the unsupervised training process of an auto-encoder. To better utilize the strengths, the methodology shifted to training the auto-encoder to recognize the sound of a chain. The current model can successfully distinguish between an unlubricated and a lubricated chain based on audio data. To accurately predict time since lubrication or chain efficiency, further work is needed Incorporating a supervised machine learning model such as a Recurrent Neural Network (RNN) may likely be a better predictive model. Once complete, the model may be able to predict the time since lubrication and/or efficiency of a bicycle chain based solely on audio data.

Project Method and Results

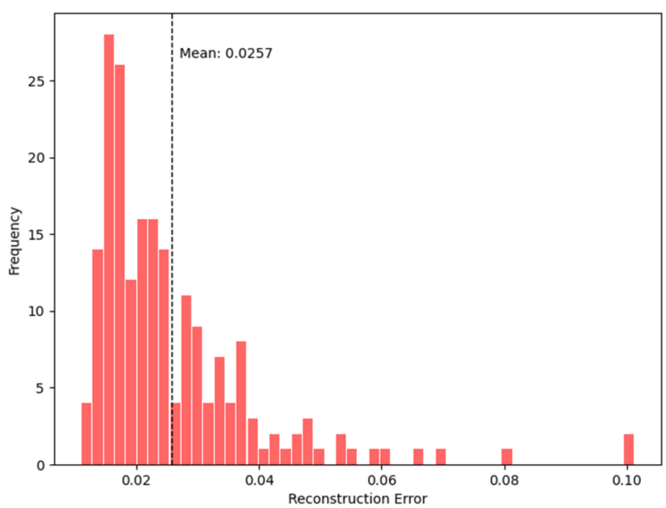
The existing chain testing rig at RESEC was outfitted with a microphone to gather audio data for each test performed. Each chain received multiple runs of tests, with a thorough clean and reapplication of lubricant between each run. These are referred to as Chain [LETTER] Run [NUMBER]. To make the data more palatable for a machine-learning model, 13 Mel Frequency Cepstral Coefficients (MFCCs) were extracted for each frame of data collected. These 13 MFCCs describe the overall shape of the sound and are commonly used in machine-learning applications. The machine-learning model chosen was an autoencoder. An autoencoder consists of two key components: an encoder and a decoder. The encoder compresses the data into the latent space representation, which is the lowest form representation of the data where the data is still recognizable. The decoder attempts to reconstruct the data back into the original format.



Project Method and Results (cont.)

The difference between the reconstructed data and the actual data is the reconstruction error. The model trained itself on a given set of data 100 times, while trying to minimize the reconstruction error. For each training dataset, the model trained on 80% of the data and validated on the remaining 20%.

Initially, the training and testing took an anomaly detection approach. To distinguish anomalies, various limits were tested on data from select chains, such as a time limit or an efficiency limit. The model was trained on data determined 'good' and tested against data determined 'bad' within a singular chain dataset. This approach led to false positives between the magnitude of reconstruction error and time since lubrication on smaller datasets when training and testing on an efficiency limit. Once these were uncovered, the methodology switched to training and testing on inter-chain datasets rather than intra-chain datasets. The model was trained on all data from Chain A Run 1, and tested against data from Chain A Run 2, Chain B Run 1, Chain A Run 1 with added artificial noise, and Chain C Run 1. Chain B had the same lubricant applied but the chain brand differed from Chain A. Chain C is the same as Chain A, but with no lubricant.



Test Set	Mean Reconstruction Error
Chain A Run 1 w/ artificial noise	0.1066
Chain A Run 2	0.0257
Chain B Run 1	0.0312
Chain C Run 1	2.0125

Fig 3. Table of Mean Reconstruction Errors when trained on Chain A Run 1 data

When tested against data from audio with no chain present, the lowest reconstruction error of 19 set a baseline for the model. These much lower reconstruction errors indicate that the model can recognize when a chain is present in an audio file. This new methodology better utilizes the strengths of an autoencoder, and the autoencoder can be used in conjunction with other machine learning models to properly predict efficiency.

- An autoencoder, due to its unsupervised training, is unable to predict the time since lubrication or chain efficiency based on audio.
- The autoencoder model can identify the presence a lubricated chain in an audio file, even with background noise present.
- The autoencoder model can de-noise given audio
- To predict chain efficiency, a supervised machine-learning model such as a Recurrent Neural Network (RNN) will be used in conjunction with the current autoencoder model.

Ray Ewry Sports Engineering Center

About RESEC

The Ray Ewry Sports Engineering Center (RESEC) is named in honor of a record-setting Olympian and College of Engineering graduate, Ray Ewry. As a joint effort between Purdue College of Engineering and Intercollegiate Athletics, the center reflects Ewry's passion for both sports and engineering and creates research and learning opportunities to athletes and students alike.

What is Sports Engineering?

Sports Engineering is a multidisciplinary field that uses engineering principles to create solutions to the greatest challenges and opportunities facing sports today. The field utilizes scientific theory, practical application, and technical knowledge to address sports-related challenges through data-driven insights and a results-oriented approach. To contribute to this field RESEC aligns it's investigations with the following priorities

EXCITEMENT

Smart Performance & Fan Experience

How can we use the latest sensors, signal processing, and analytics to improve athlete performance and improve engagement with fans?

INTEGRITY

Fairness, Accessibility & Social Integration

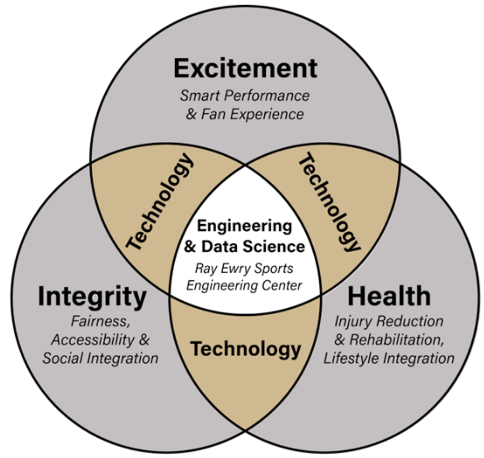
As technology in sports grows, what are the limits of human judgement, and how do we develop technology to ensure a level playing field?

HEALTH

Injury Reduction & Rehab, Lifestyle Integration

What aspects of advanced healthcare and science can be engineered into solutions for sports rehabilitation and performance?

Every sport must balance these priorities to create the best experience for all. RESEC searches for the technology to fill the gaps between each priority and facilitates collaborative research across Purdue through the application of engineering and data science



Research Technology Platforms

RESEC categorizes industry partners and academic affiliates into the following technology platforms for scaling and implementation to streamline collaboration.

- **Smart Materials for Performance and Safety**
- **Accessible Technology for Societal Integration**
- **Equipment Design for Athlete Feel and Control**
- **Intelligent Prototyping for Rapid Development**
- **Digitalization of Sports Ecosystems**
- **Spectator Experience and Fan Engagement**

When ideas arise from industrial partners or internal faculty affiliates, RESEC facilitates the operations necessary turn opportunities into action.

Education Offerings

Purdue's academic prowess offers a unique opportunity to engage talented students, staff and faculty members with sports engineering. In addition to research opportunities for undergraduate and graduate students, RESEC is proud to offer the first comprehensive Professional Masters Concentration in Sports Engineering in the United States. With these capabilities, we are equipping the next generation of sports engineers to redefine what's possible.

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