IDEA

Innovations Deserving
Exploratory Analysis Programs

Rail Safety IDEA Program

Development of a Prototype Smart Hy-Rail Wheel

Final Report for
Rail Safety IDEA Project 49

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August 2024

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IDEA Project RS-49

Prepared for

The Rail Safety IDEA Program
Transportation Research Board
National Academies of Sciences, Engineering, and Medicine

by

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- Amtrak for providing a hy-rail vehicle and track access at their Wilmington yard to dry-run data acquisition
- Railworks, Inc. for providing a hy-rail track geometry truck and donating two days of inspection time to collect sensor and ground truth data for this research
- MDDE short line railroad for providing track access at sites in NJ and DE for collecting the data necessary to evaluate this concept

Glossary

AI	Artificial Intelligence
CFR	Code of Federal Regulations
CNN	Convolutional Neural Network
ECU	Electronic Control Unit
FRA	Federal Railroad Administration
IMU	Inertial Measurement Unit
MAE	Mean Absolute Error
MEMS	Microelectromechanical System
ML	Machine Learning
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RTK-GPS	Real Time Kinematic Global Positioning System
TGC	Track Geometry Car

EXECUTIVE SUMMARY

The Federal Railway Administration track safety standards require rigorous visual inspections of tracks based on their operating speed (FRA track class) [1]. These inspections can be as frequent as twice per week. Often these inspections are carried out using hy-rail (highway/rail) vehicles, with the trained inspector using a set of hand tools (track level, string line, gauges, etc.) to further measure locations that appear to be out of compliance. In addition, railways perform specific inspections using hy-rail or rail bound equipment to measure track geometry, internal rail condition, track strength, tie condition, ballast condition, joint bar condition, etc. These vehicles are expensive to build, maintain and operate.

Currently, bolt-on inspection systems for use on inspector's hy-rail vehicles such as track geometry measurement systems, can be used to assist and supplement the inspector, but are also quite expensive. Such inspections are crucial to maintaining a safe operating environment. The objective of this research was to develop a prototype, low-cost, "smart" hy-rail wheel (SmartWheel) to be deployed on an inspector's hy-rail vehicle (or any hy-rail vehicle the railway operates) that assists the trained inspector in identifying locations in track with certain classes of potential defects, in an autonomous and passive manner. It is intended that the SmartWheel be self-contained, autonomous, and provide alerts to the operator. Additionally, the SmartWheel must be inexpensive to implement and provide additional information to the inspector to assist in assessing particular elements of the track condition.

The innovative approach described herein utilizes a low-cost inertial measurement unit (IMU) integrated into the hy-rail gear along with a combined mechanistic and artificial intelligence (AI) approach to analyzing the response data from the IMU to identify particular classes of track defects (or issues). These include, but are not limited to, profile/surface, cross level, alignment, dipped joints, rail surface defects, rail corrugation, mud spots, etc. This differs significantly from a hy-rail based track geometry system in that it does not require a sophisticated algorithm for transforming the IMU data to measurable geometry parameters (which requires additional expensive hardware). Rather, the system evaluates the IMU response data directly using AI algorithms developed as part of this research. The current status of the product addresses a subset of track geometry parameters.

A research program was initiated that consisted of the following steps:

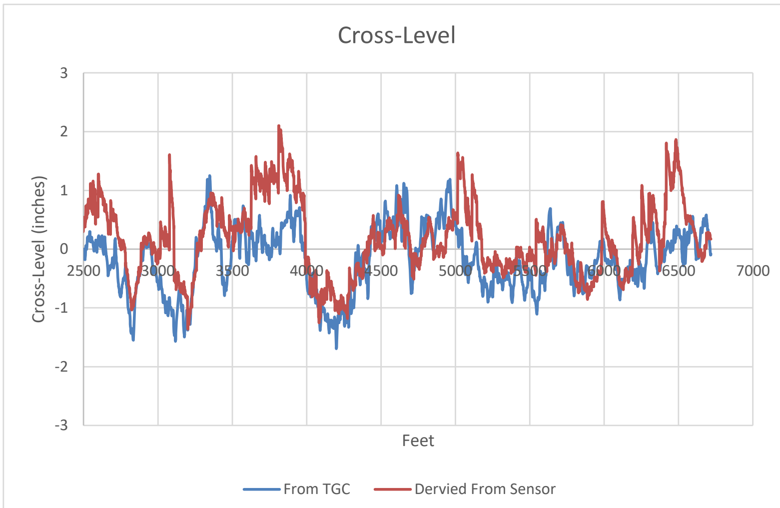
1) Identifying a suitable low-cost IMU that was accurate and reliable enough to support the measurement environment
2) Perform limited data acquisition onboard a hy-rail inspection vehicle outfitted with a track geometry system to provide ground-truth data to prove the concept and develop a first-generation AI/Deterministic system
3) Develop a prototype AI/Deterministic algorithm to address a subset of track geometry parameters
4) Validate the approach with the data acquired
5) Develop next steps for a field deployable prototype to undergo further testing and validation

The data acquisition plan resulted in a dataset of ground-truth track geometry parameters, and corresponding SmartWheel sensor data (one sensor on each of the lead guide wheels of the hy-rail vehicle). This data was collected on two short-line railways for approximately 50 miles of track. Independent acquisition of each sensor (left and rail guide-wheel), as well as a lack of a speed sensor connected to the SmartWheel sensors offered challenges in aligning the data that had to be overcome by correlating the SmartWHeel sensor data with the speed from the track geometry system, i.e., acceleration went to zero for a period of time when the vehicle was stationary.

Once the SmartWheel sensor data was collected, filtering algorithms were researched and employed to remove the high frequency noise associated with wheel/rail roughness, which left the portion of the signal that depicts the vehicle response to the track geometry. This data was the used to develop prediction models. Two types of models were evaluated; 1) machine learning using a windowed approach with a Convolutional Neural

Network (CNN, and, 2) deterministic approach using data fusion which consists of integration and a complimentary filter to take advantage of the IMU quasi-static and kinematic signal outputs.

The dataset was split for training, testing and validation. The results of the models showed that the sensor data is appropriate for defining a subset of track geometry parameters and conditions. A sample visualization of cross-level (the height difference of one rail to another in the transverse plane of the track) is shown in the figure below:



While some location showed good agreement of the data, others showed some significant error. This error was likely introduced due to the lack of speed data from the data acquisition activity. A comparison of error values from ground truth for each of the modeling approaches is shown in the table below for three specific track geometry parameters:

Parameter	Deterministic	Machine Learning
Cross Level	0.83 inches	0.32 inches
Degree of Curvature	0.37 degrees	0.22 degrees
Surface	0.57 inches	0.46 inches

The primary benefit of this product is a safer operating environment through the low-cost implementation of a tool that assists inspectors in an autonomous fashion in locating potential track defects. A secondary benefit is identifying locations with habitual problems where revised maintenance practices can increase safety and reduce overall costs. Lastly, successful implementation of this research will help inspectors (particularly less experienced inspectors) identify locations that are sometimes quite difficult to quantify, or even recognize, visually. This includes finding locations requiring remediation identified by stand-alone inspection cars. Not all track anomalies are identifiable through this technology, but a significant number of safety related anomalies are identifiable.

While the research to this point shows promise, there are still several tasks that need to be accomplished to provide a field demonstrable prototype which include: incorporation of a speed signal and RTK-GPS signal to the SmartWheel sensor, additional field testing with a hy-rail vehicle outfitted with a track geometry system to gather more comprehensive track condition data to further train the AI models, and implementation of an inexpensive camera-based gage referencing system.

The implementation and use of the final system will be seamless for the railway inspectors. It is expected that this system will eventually be integrated directly into manufacturer's hy-rail gear as a low-cost option, or even become "standard." The information will eventually be relayed to the inspector via mobile phone app for immediate consumption.

IDEA PRODUCT

The Federal Railway Administration track safety standards require rigorous visual inspections of tracks based on their operating speed (FRA track class) [1]. These inspections can be as frequent as twice per week. Often these inspections are carried out using hy-rail (highway/rail) vehicles, with the trained inspector using a set of hand tools (track level, string line, gauges, etc.) to further measure locations that appear to be out of compliance. In addition, railways perform specific inspections using hy-rail or rail bound equipment to measure track geometry, internal rail condition, track strength, tie condition, ballast condition, joint bar condition, etc. These vehicles are expensive to build, maintain and operate.

Currently, bolt-on inspection systems for use on inspector's hy-rail vehicles such as track geometry measurement systems, can be used to assist and supplement the inspector, but are also quite expensive. Such inspections are crucial to maintaining a safe operating environment.

The objective of this research was to develop a prototype, low-cost, "smart" hy-rail wheel (SmartWheel) to be deployed on an inspector's hy-rail vehicle (or any hy-rail vehicle the railway operates) that assists the trained inspector in identifying locations in track with certain classes of potential defects, in an autonomous and passive manner. This SmartWheel would be self-contained, autonomous, and provide alerts to the operator. Additionally, the SmartWheel would be inexpensive to implement and provide additional information to the inspector to assist in assessing particular elements of the track condition.

The innovative approach described herein is to utilize a low-cost inertial measurement unit (IMU) integrated into the hy-rail gear along with a combined mechanistic and artificial intelligence (AI) approach to analyzing the response data from the IMU to identify particular classes of track defects (or issues). These include, but are not limited to, profile/surface, cross level, alignment, dipped joints, rail surface defects, rail corrugation, mud spots, etc. This differs significantly from a hy-rail based track geometry system in that it does not require a sophisticated algorithm for transforming the IMU data to measurable geometry parameters (which requires additional expensive hardware). Rather, the system evaluates the IMU response data directly using AI algorithms developed as part of this research. The current status of the product addresses a subset of track geometry parameters, due to the time and budget constraints of the project undertaken herein.

The primary benefit of this product is a safer operating environment through the low-cost implementation of a tool that assists inspectors in an autonomous fashion in locating potential track defects. A secondary benefit is identifying locations with habitual problems where revised maintenance practices can increase safety and reduce overall costs. Lastly, successful implementation of this research will help inspectors (particularly less experienced inspectors) identify locations that are sometimes quite difficult to quantify, or even recognize, visually. This includes finding locations requiring remediation identified by stand-alone inspection cars. Not all track anomalies are identifiable through this technology, but a significant number of safety related anomalies are identifiable.

The implementation and use of this system will be seamless for the railway inspectors. It is expected that this system will eventually be integrated directly into manufacturer's hy-rail gear as a low-cost option, or even become "standard." The information will eventually be relayed to the inspector via mobile phone app for immediate consumption.

CONCEPT AND INNOVATION

Track geometry defects are defined as deviations from design exceeding a defined limit, where the limits are assigned as a function of allowable operating speed, organized by FRA track class. These limits are contained in the FRA Track Safety Standards. [1] While these regulations cover all aspects of the track, including rails, ties, ballast, geometry, special trackwork and surrounding right of way, the focus of this research was on a subset of track geometry parameters. The parameters investigated included surface, cross-level, curvature, and super elevation as the sensors measure wheel response associated with these parameters. Briefly, surface is the vertical running surface of the rail typically measured using a 62' chord; cross-level is the elevation difference from one rail to the adjacent rail, perpendicular to the running axis of the track; curvature is the radius of the curve; super elevation is the design elevation difference from one rail to the adjacent rail. More can be found on these measurements and other in reference [2-4].

Typically, track geometry is measured using a heavy rail vehicle that uses a system of lasers and an Inertial Measurement Unit (IMU) to compute the exact measurements under load for each foot of track travelled. These manned cars are deployed on mainline track and can travel heavily used main lines up to four times per year. Railways have started to incorporate autonomous systems installed on a locomotive, freight car or passenger car that collects data whenever the vehicle is in a train consist and moving. This can result in track geometry data collected as frequently as multiple times per week. However, railroads are still required to provide visual inspection of the entire track using trained inspectors (often termed manual inspection). Depending on the speed of the track, this may be required up to two times per week [1]. These inspectors will travel their territory in a hy-rail (highway and rail) vehicle and visually inspect the track. If they suspect a defect exists, they will go on track and measure/verify using handheld tools such as a track level, string line, tape measure, etc. Expensive, bolt-on track geometry measurement systems are available for hy-rail vehicles, but the opportunity exists for a low-cost and innovative solution.

The concept investigated as part of this research was to employ a low-cost MEMS IMU incorporated into the hy-rail gear to measure wheel response to the track input and to develop an artificial intelligence (AI) interface based on machine learning (ML) principles to predict the existence of track geometry defects on the traversed track.

Triaxial IMUs measure acceleration and angular rate of rotation in three dimensions and can be programmed to acquire data at various frequencies. This data is typically noisy and is traditionally transformed to the frequency domain for analysis. While this approach is used for modern track geometry systems, significant computational resources are required to filter and transform the data, and sophisticated algorithms for integrating the data are required to convert the raw acceleration data to typical linear measurements which a track engineer is familiar with. Using ML techniques to train an algorithm alleviates the need for this additional onboard computing power.

The resulting innovation of the SmartWheel is a passive system that is autonomous and doesn't require constant monitoring.

INVESTIGATION

This investigation was conducted in two stages, with nine associated tasks, as shown in TABLE 1.

TABLE 1. Project task list

	Tasks	% Completed
	Stage 1. Hardware Implementation and Data Acquisition	
Task 1	Kickoff Meeting with Expert Panel	100%
Task 2	Hardware Design and Implementation	100%
Task 3	Data Acquisition	100%
Task 4	Data Pre-Processing and Filtering	100%
Task 5	Stage 1 Report and Project Progress Review	100%
	Stage 2. Development of AI Interface and Validation	100%
Task 6	Development of AI Interface	100%
Task 7	Preliminary Validation	100%
Task 8	Prototype Specification	100%
Task 9	Prepare Final Report	100%

TASK 1. KICKOFF MEETING WITH EXPERT PANEL

An expert panel was assembled made up of leading industry experts and is presented in TABLE 2 below.

TABLE 2. Expert advisory panel

Name	Affiliation	Title	E-Mail
Brad Kerchof	ARM/NS (retired)	IDEA Technical Expert	bradkerchof@gmail.com
Stephen Love	CSX	Technical Director	Stephen_Love@csx.com
Rich Scheiring	AMTRAK	Director Clearances, Inspection & Testing	wesley.scheiring@amtrak.com
Chris Hartsough	HARSCO Rail	Track Engineering Team Lead	chartsough@harsco.com
Bernhard Metzger	ENSCO	Director Solutions Engineering	Metzger.Bernhard@ensco.com

The expert panel met on November 29, 2022. A presentation was made to identify the roles of the advisory panel, describe the project timeline, and highlight the major objectives and work tasks of the project. After the PI presented the project, an interactive discussion was held with the panel. After several technical clarifications, the panel agreed on and approved the program approach. The panel is extremely interested in the results of this research, as it offers some real potential for improving local track inspection for both large and small railways. A summary of major comments is as follows:

1) With autonomous inspection gaining increased utilization with the large freight railroads, such a system would be ideal for locating spots requiring maintenance. Several channels of information would likely benefit all track inspectors during their routine inspections.
2) Regional and short-line railroads typically do not have the same access to automated geometry testing as the Class 1s. These smaller railroads would likely benefit from the automated inspection capability that this hy-rail mounted system offers.
3) The proposed sensors are remarkable in their capabilities (acquisition rate and accuracy) for the price.
4) All of the panel members offered time and equipment for further testing/validation using their own inspection platforms as available.

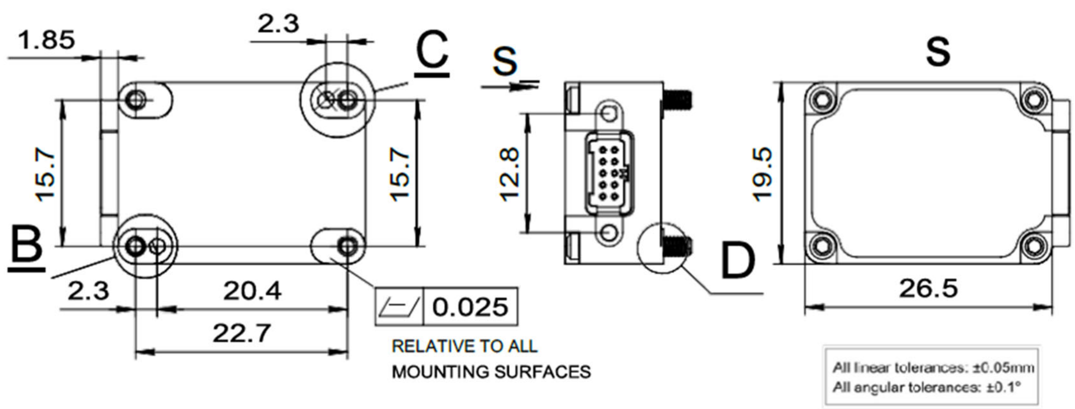
TASK 2, HARDWARE DESIGN AND IMPLEMENTATION

Following a careful study of available sensors, a set of potential candidate sensors were identified and evaluated. The pre-identified sensors were chosen based on their acquisition rates, limits, and accuracy as a function of the cost. Using available instrumentation data previously collected by the researchers (and advisory panel members), the research team defined the specific sensor features needed as well as the best cost to feature relationship. The final selection was the Inertial Labs KERNEL-110 IMU with a range of +/-8 g's which is sufficient to provide the necessary sensitivity in measurement. These sensors provide 3-axis acceleration data and 3-axis gyroscope data at 2,000 Hz with a high degree of accuracy.

In addition, service cables and data acquisition cables were specified to provide power to the sensors and extract data from the sensors over an RS-422 interface.

Two complete sets of sensors and cables were ordered and were delivered the week of January 16, 2023.

The preliminary mounting bracket design was completed and manufactured by the University of Delaware's (UD) machine shop. The sensors are 26.5mm x 19.5mm with M2-4 standoffs as shown in **FIGURE 1** below. As the sensor housings are aluminum, a 28mm x 28mm x 6mm thick piece of steel was cut, and holes drilled and countersunk to accept the M2-4 bolts which will be attached to the standoffs with nuts and Loctite. The mated steel plate will be used to attach the sensors to the wheel bearing housing using magnets. This approach is being deployed as this is a temporary installation for data acquisition purposes only. Permanent mounting and implementation will be investigated during a future commercialization process.



a) Bottom view b) Side view c) Top view

FIGURE 1. Sensor mounting screw configuration. a) hole layout for mounting plate drilling, b) cable connector location, c) overall sensor dimensions

TASK 3. DATA ACQUISITION

Data acquisition was separated into bench testing and simple sensor response testing, followed by a comprehensive data acquisition test using a hy-rail track geometry inspection vehicle.

Bench Testing and Simple Sensor Response

Bench testing of the data acquisition system was completed in the office. This consisted of connecting the sensors with the supplied cable set and collecting data at various acquisition rates using the data acquisition software supplied by the sensor manufacturer. In this manner, it was determined that the sensors responded appropriately and data could be successfully acquired.

A preliminary data acquisition trip was conducted on Amtrak's Wilmington Yard house track to verify the sensor response on a typical hy-rail vehicle. **FIGURE 2** below shows a track chart and map of the overall location. Approximately 0.5 miles of track was traversed.

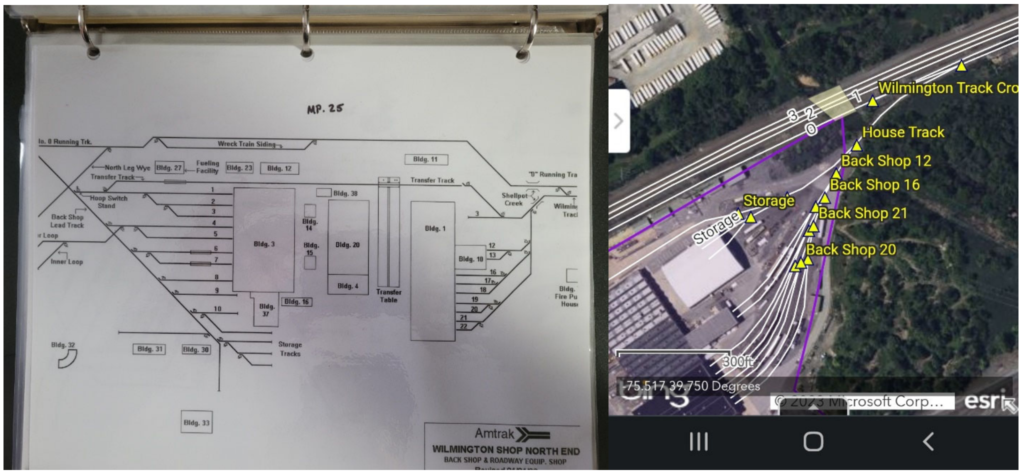


FIGURE 2. Sensor response data acquisition location

Seven runs were made over the half mile as shown in TABLE 3, with one sensor on the rear guide wheel of the vehicle (passenger side), tethered to the laptop, and operated from the rear of the cab. The left side of **FIGURE 3a** shows the sensor screwed to the steel plate and attached to the mounting magnet. This figure also shows the axis orientation of the sensor, where *y* is in line with the cable connector, *x* is perpendicular to the cable connector, and *z* is vertical. **FIGURE 3b** shows the location of the sensor in the proximity of the wheel.

TABLE 3. Test run glossary

Num.	Direction	Speed	Frequency
1	Forward	5 mph	500 Hz
2	Reverse	5 mph	500 Hz
3	Forward	5 mph	2,000 Hz – Aborted
4	Forward	5 mph	1,000 Hz
5	Reverse	5 mph	1,000 Hz
6	Forward	5 mph	2,000 Hz
7	Reverse	5 mph	2,000 Hz

a) Sensor mounting configuration

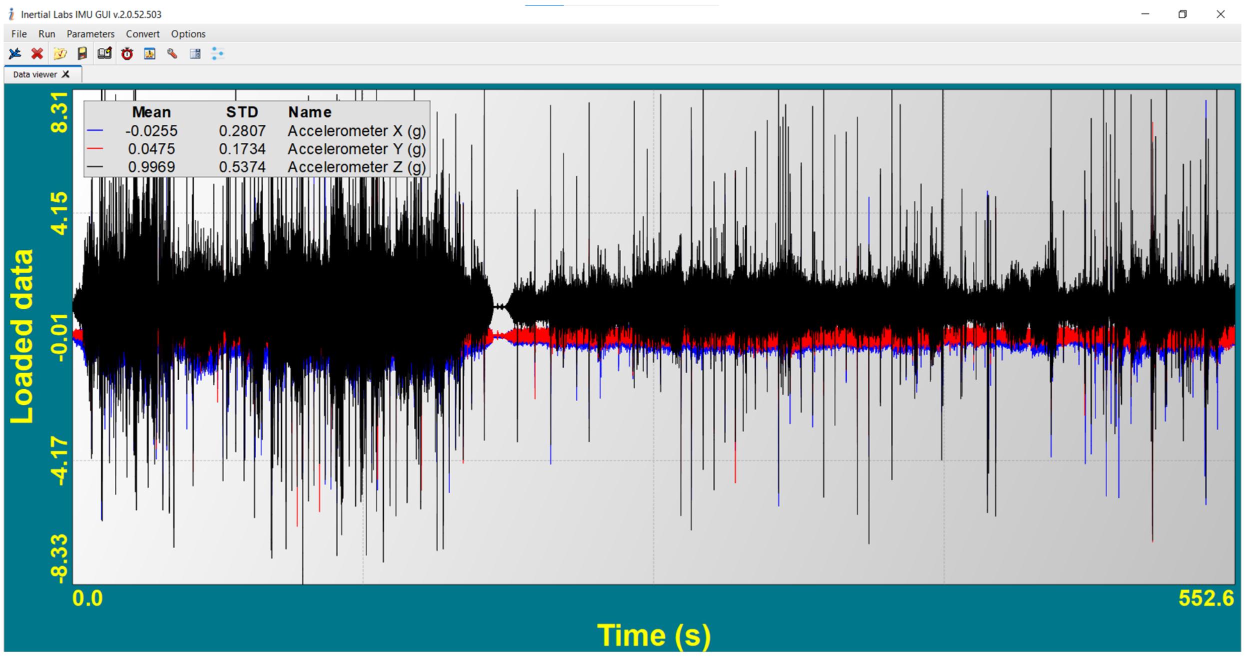
b) Sensor tethering to rear of cab

FIGURE 3. Sensor mounting configuration and tethering to laptop

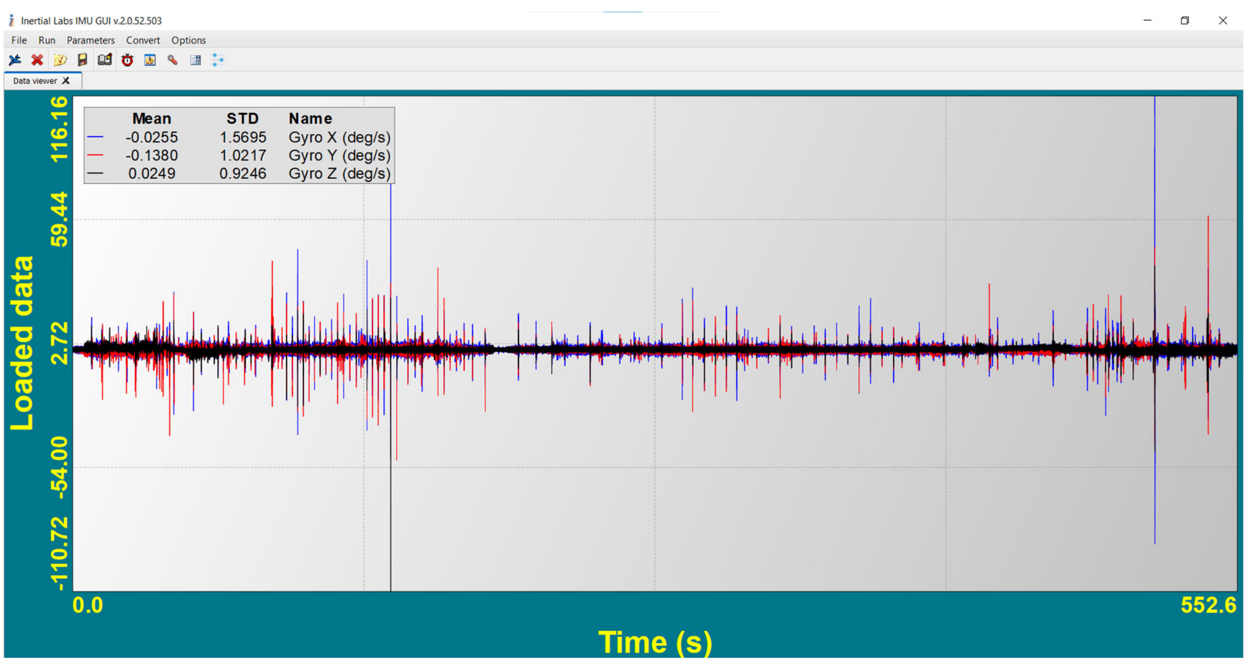
FIGURE 4 shows the sensor response data for the three axes of acceleration and gyroscope for Run 7. Note that the mounting orientation of the sensor (cable facing to the rear of the vehicle) resulted in the following[1]:

x-axis: Lateral (positive towards the passenger side; perpendicular to track)
y-axis: Longitudinal (positive forward; in-line with track)
z-axis: Vertical (positive down; towards the ground)

[1] Note that the installation for this simple test was different than the data acquisition test (discussed in the next section) where the sensors were rotated 90 degrees to accommodate the cabling during mounting on the front wheels



a. Three axes of acceleration



b. Three axes of gyroscope

FIGURE 4. Sensor response data for run 7

The data acquisition on Amtrak verified that suitable sensor response data could be acquired at varying speeds and data acquisition rates.

Comprehensive Data Acquisition in Conjunction with a Hy-Rail Track Geometry Inspection Vehicle

The data acquisition activity on a track geometry inspection vehicle was conducted using a Railworks supplied hy-rail vehicle and track on two local shortline railways; the Maryland & Delaware (MDDE) railway and the Black River & Western (BRW) railway. Railworks generously sent a hy-rail track geometry inspection vehicle and operator to the MDDE, who donated track and time, along with a pilot for two days of testing. The first test was conducted on the MDDE on 7/25/23 near Selbyville, DE and the second day of testing was conducted on the Black River & Western (BRW) railway on 7/27/23 near Ringoes, NJ. Each location provided approximately ten miles of track of varying condition and layout.

At the beginning of each day, the sensors were mounted on the Railworks Track Geometry truck on the front hy-rail gear as close to the wheel as possible, and the cables tethered to the laptop, secured with zip ties. Each sensor was mounted with a magnet on the steel plate supporting the rail sweep. They were secured for safety using zip ties. Figure 5 shows the sensor installation and cable tethering.

FIGURE 5a shows the general sensor mounting and cable tethering to the passenger seat in the front of the cab. The contact gage system used for the track geometry measurement system can also be seen in this figure.

FIGURE 5b and **FIGURE 5c** show the sensor mounting configuration for each side of the vehicle. Note that the sensors were 180 degrees out of phase to accommodate secure cabling, i.e, the cables for each sensor point away from the wheel towards the centerline of the track. This results in opposite signs for the lateral and longitudinal channels of each sensor. This was addressed and the data properly oriented (correct sign convention) during analysis.

Note that for this mounting configuration, the positive acceleration and angular velocity values about the defined axis are defined as follows:

x-axis: Longitudinal (inline with the track)
- positive forward for driver’s side sensor
- negative forward for passenger side sensor

y-axis: Lateral (perpendicular to the track)
- positive toward driver’s side for driver’s side sensor
- positive toward passenger’s side for passenger side sensor

z-axis: Vertical
- positive down, towards the ground

a) Front of vehicle showing cabling and contact gage measuring system

b) Passenger side sensor

c) Driver's side sensor

FIGURE 5. Sensor installation and cable tethering. Note the sensors are mounted in the opposite direction laterally/longitudinally.

The track was tested, and data was captured independently by the Railworks' track geometry system and the two SmartWheel sensors. The track geometry data, captured in the distance domain, was collected every foot of vehicle travel. This data was stored in the track geometry system processor and downloaded for later use in the next stage of this research. The sensor data was captured for each sensor on a separate processor in the time domain at a frequency of 1,000 Hz (1,000 sensor samples per second). On day one, the track was tested in the increasing milepost direction. On day two, the track was initially tested in increasing milepost direction, then the truck was turned around and the track was retested in decreasing milepost direction. This resulted in approximately 30 miles of sensor and corresponding track geometry data collected, in two different datasets, from two different measurement systems. A typical output from the Railworks hy-rail track geometry measurement system is shown as a plot in **FIGURE 6**. Note this data can be exported to an ASCII file format for further analysis, to be achieved in Stage 2.

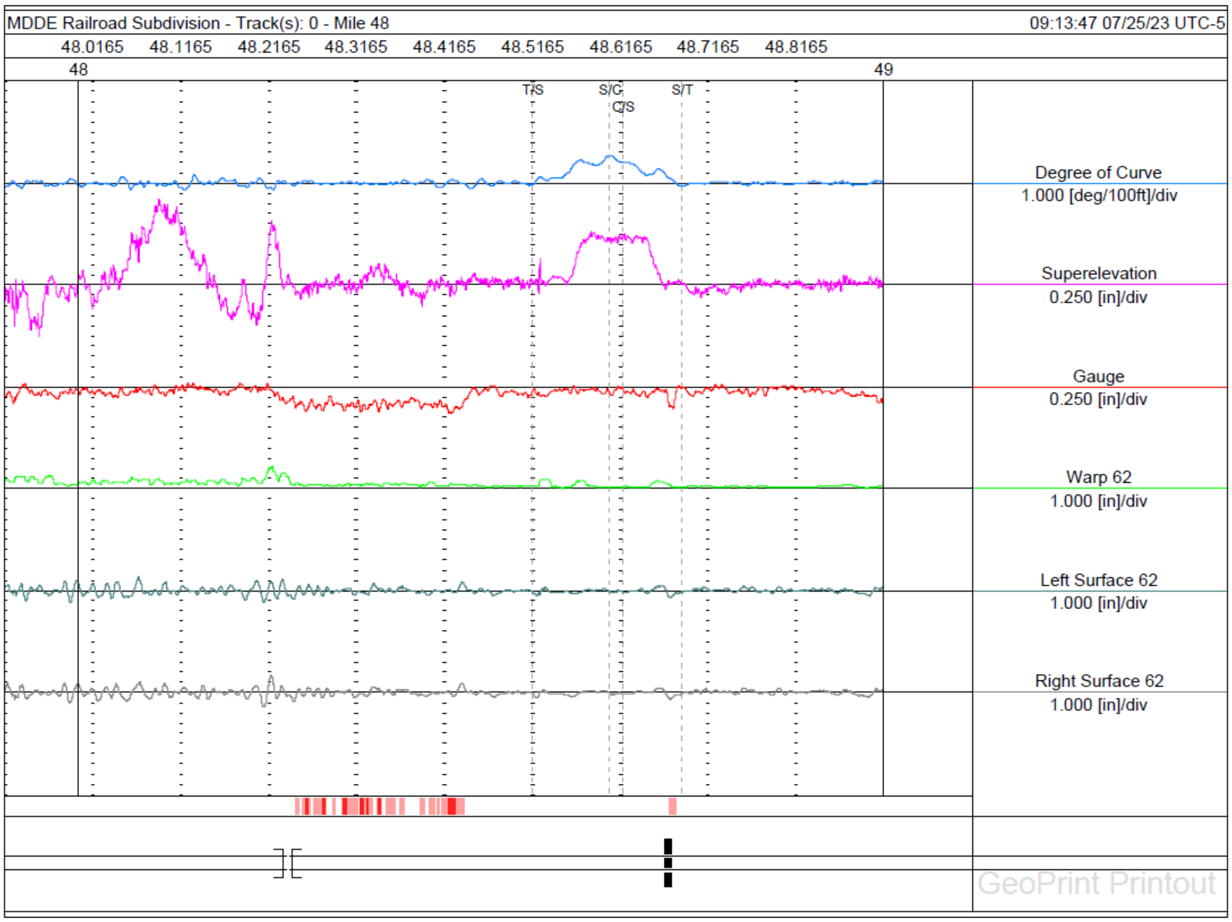


FIGURE 6. Typical track geometry plot output[2].

It should be noted that periodically, the driver's side SmartWheel sensor lost connection and froze up, requiring restarting of the sensor data acquisition system. Discussion of data preprocessing and filtering follows.

TASK 4. DATA PRE-PROCESSING AND FILTERING

The data from the track geometry measurement system (as shown in **FIGURE 6**) was exported in ASCII format and was represented spatially for each foot of track. The data components for each foot included milepost, GPS coordinates, testing speed, and more than 50 channels of track geometry output. Separately, the data from

[2] The track geometry and gauge output shown in Figure 6 is from an existing (and considerably more expensive) track geometry measurement system.

the SmartWheel sensors was captured in the time domain at frequencies of up to 1,000Hz. This data included (for each time step) three axes of acceleration, three axes of rotational velocity, and several derived channels (as shown in **FIGURE 4**).

This resulted in two separate datasets (captured by two different systems) to be used for analysis that required pre-processing, including alignment and filtering.

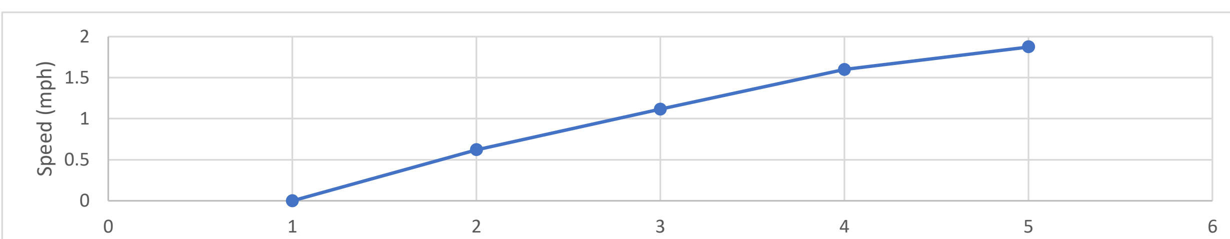
Data Pre-Processing

In order to properly analyze the data, several pre-processing steps were required to align the data for model development. Data acquisition for the sensor data was performed using the software provided by the sensor manufacturer. This software was limited in that it could only capture one sensor at a time. Thus, two instances of the software were launched on the laptop, one for each sensor. Due to the time required for a human to start both sensor's data collection, a short time lag (< 3 seconds) could be seen in the written data sets. The data from each sensor was evaluated and the time lag shift corrected to align the sensor data in the time domain.

Since the data from the track geometry inspection vehicle was captured spatially and the sensor data was captured in the time domain, the data from the different systems had to be aligned to ensure the time windows were representative of the spatial output. This was done using the testing speed variable in the track geometry output data. In this manner, the number of time samples in a window of defined length could be determined. **FIGURE 7** shows a representation of the data overlaid in the spatial domain for the hy-rail track geometry output, and the converted time domain sensor data, for comparative purposes.

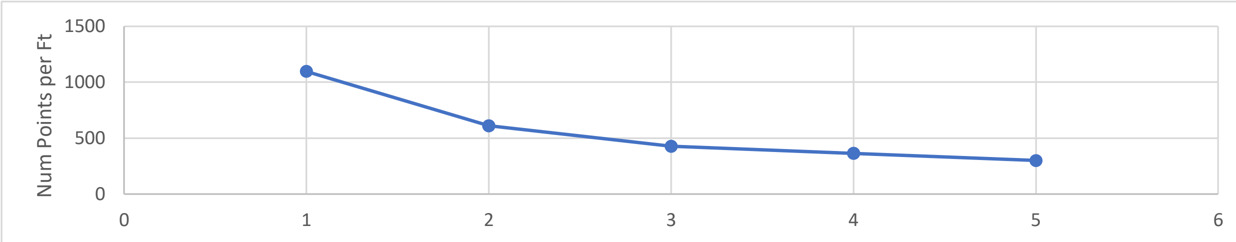
FIGURE 7 is intended to show that as speed increases, the number of sensor points available for analysis decreases. **FIGURE 7a** shows the starting point of an inspection where approximately 1,000 points of sensor data are collected per foot (horizontal axis foot 2, speed 0.7 mph) and as the speed increases, the number of points per foot reduces to approximately 333 per foot (foot 5, speed 2 mph). This is demonstrated in **FIGURE 7b**, where the number of points acquired by the sensor decreases with increases in speed. At upper speeds of 25 mph, the number of sensor points per foot would be 27[3]. This will be accounted for in model development. Further, vibration increases with increased speed as expected, and the large deviations are due to changes in input geometry.

FIGURE 7c shows the acceleration data captured by the sensor. Each color represents a window of acceleration points associated with one foot of measured track geometry data. The density of points decreases with increases in speed.

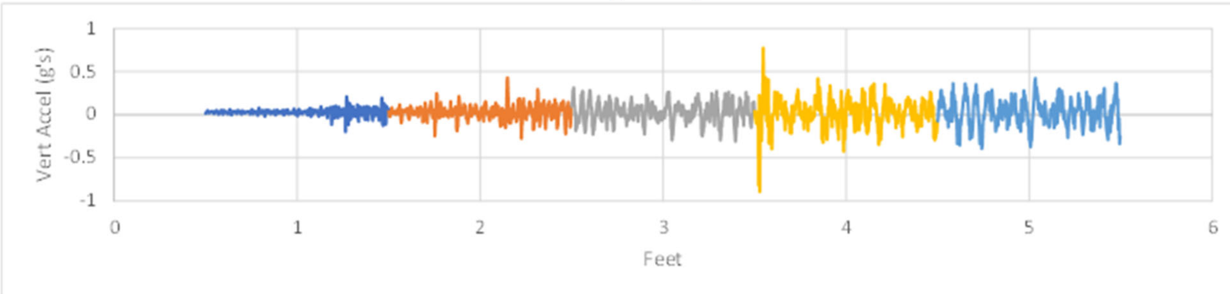


a) Hy-rail speed

[3] Note that 27 points is sufficient for this type of analysis. For the purposes of this study, 25mph is considered the maximum speed. Should a second generation be developed for higher speeds, the sensors can be programmed to acquire data at 2,000 Hz.



b) Number of sensor points per foot of travel



c) Vertical acceleration from sensor at 1,000 Hz

FIGURE 7. Sensor data as a function of speed travelled

Aligning the data for purposes of this research was quite challenging. Without a distance input to the sensors, a post alignment was achieved. The track geometry data (ground truth) was provided in the distance domain and had an accompanying speed channel for each foot of data collected (top plot in **FIGURE 8**). The sensor data was collected in the time domain, thus the number of sensor readings vary as a function of speed. When the vehicle stops (zero speed), the acceleration becomes static (bottom plot of **FIGURE 8**). Aligning these locations, and using interpolation, the specific time based sensor points were synchronized with the distance based geometry points for each foot of track measured. It is recognized that this introduces some linear offset error, which can be corrected with a distance input device to the sensor data acquisition.

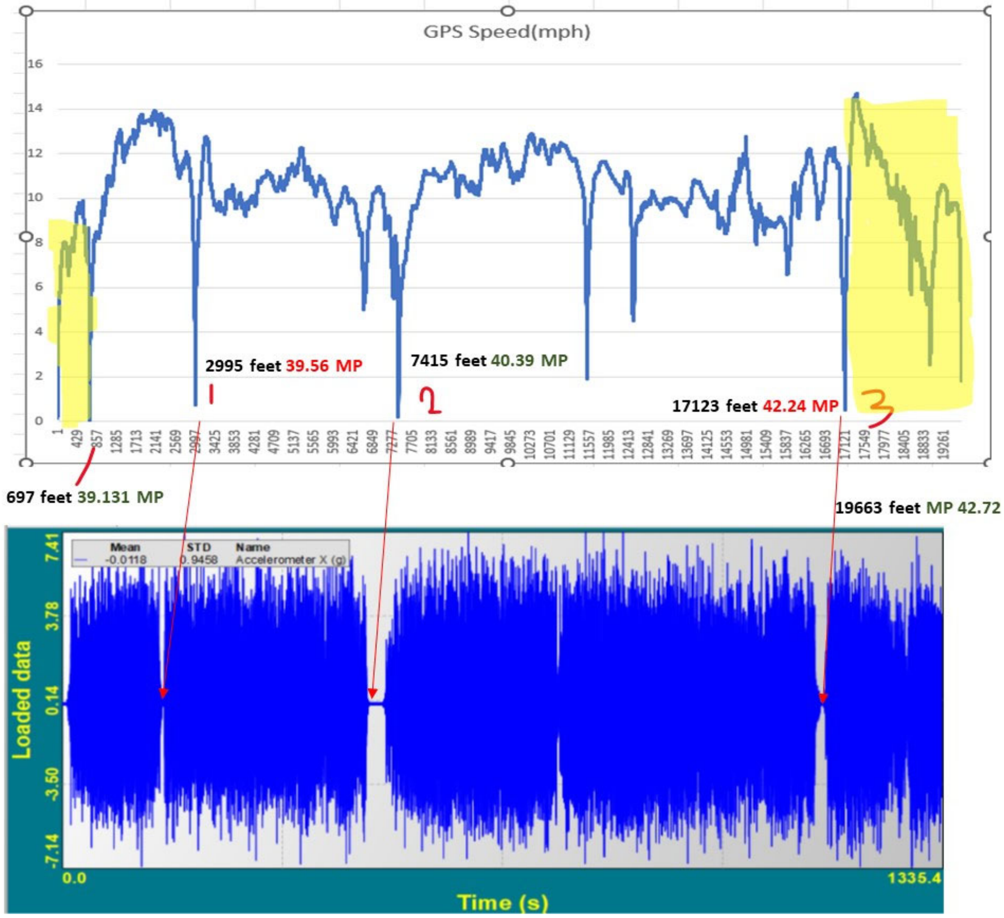


FIGURE 8. Alignment of data using speed and zero acceleration markers

Data Filtering

The sensors are subject to high frequency vibration due to their location, and as such, the response data requires suitable filtering to isolate those portions of the signal that reflect the track geometry response. Several filtering techniques were evaluated in this task to isolate signature data to be used in model development.

The first filter utilized was the Fast Fourier Transform (FFT), which converts the time domain sensor data into the frequency domain. **FIGURE 9** shows an example of the resulting frequency spectrum for 4.1 seconds of collected data.

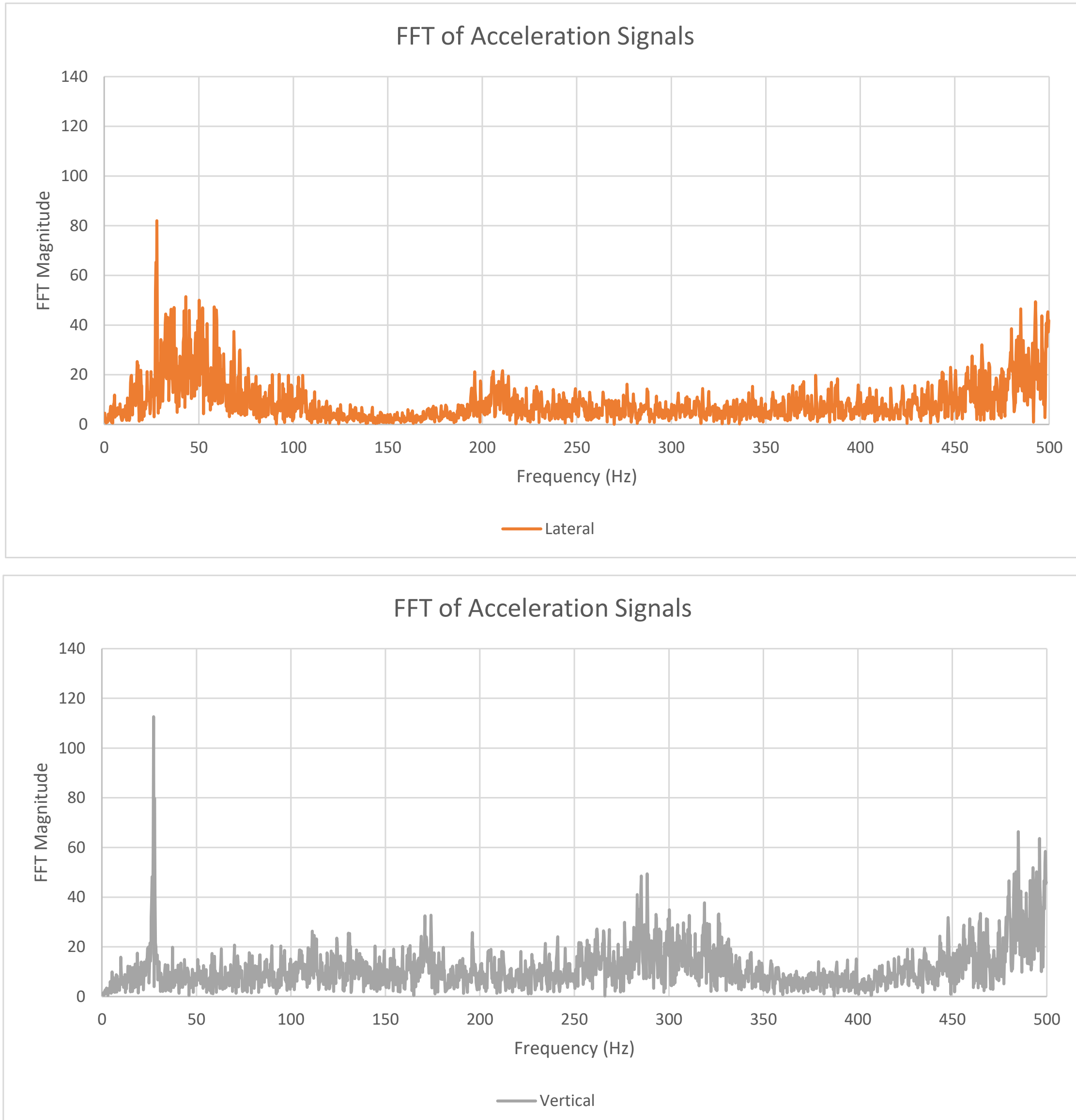
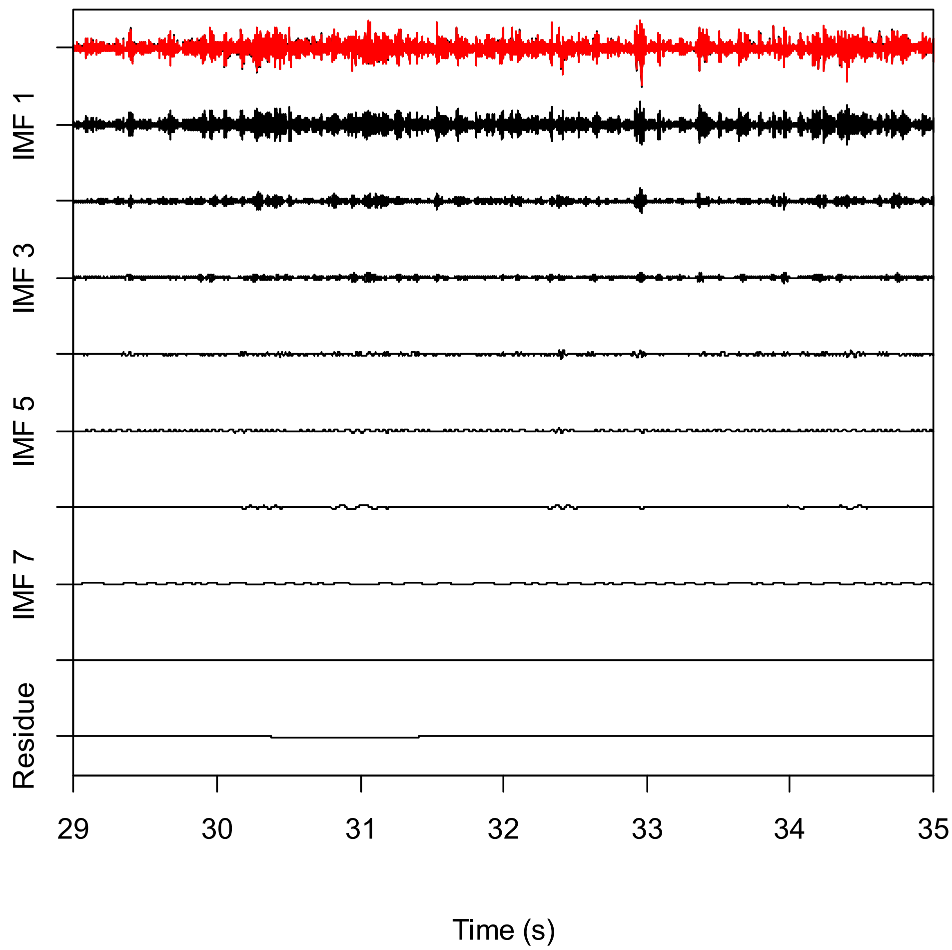


FIGURE 9. FFT results for the lateral and vertical accelerations of the passenger side sensor

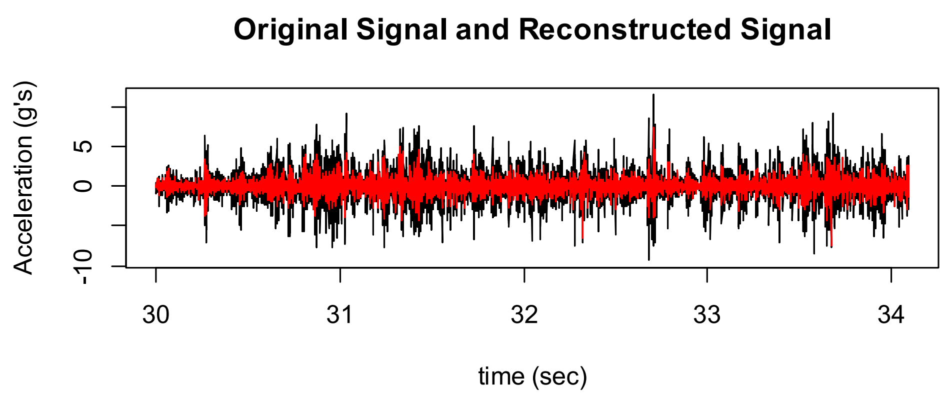
This figure clearly shows dominant frequencies in the lateral and vertical planes. Note the spike at 27 Hz. This frequency is associated with engine vibration, as it could be seen when the vehicle was stationary. Except for engine vibration, the higher frequencies are associated with vibration at the wheel due to wheel/rail roughness (short wavelength anomalies on the rail and/or wheel) and other input sources, while the lower frequencies are generally associated with displacement. This will be further evaluated as part of Stage 2.

The frequency data can be used to generate a filtered acceleration response by applying a band-pass frequency filter (excluding frequency components not of interest, such as higher frequency vibrations) and using only the frequencies of interest. Using the Inverse Fast Fourier Transform (IFFT), and the frequencies of interest, as well as their corresponding magnitudes and phase shifts, the signal of interest can be reconstructed.

The second filter investigated was the Hilbert Huang Transform (HHT). This filter decomposes the signature into a number of Intrinsic Mode Functions (IMF) and is especially powerful for nonstationary/nonlinear real-world data. Each IMF represents a portion of the signal such that the number of extreme values and zero-crossings are equal. **FIGURE 10a** shows an example of an initial application of the HHT to the vertical acceleration signal. The trace in red is the original signal. The subsequent traces are components of the decomposed signal (IMFs and the residue). Note that the vertical scale (in g's) is the same for each IMF, thus activity appears shallow for each additional IMF. Considering the first three IMFs as high frequency noise, the reconstructed signal in red (removing IMFs 1-3 from the original signal) overlaid with the original signal in black, is shown in **FIGURE 10b**. This results in an acceleration input signal that has high frequency vibration and impact spikes removed. These results are promising but still very preliminary. A more extensive analysis, to include identifying the number of IMFs corresponding to noise, will be further performed in the Stage 2 work.



a. Raw acceleration signal and IMFs (decomposed signal)



b. Raw acceleration signal and denoised signal (removing IMFs 1-3)

FIGURE 10. HHT application.

The above filtering approaches were evaluated, along with several others, for multiple window lengths in time and distance. The preferred window length, as well as additional filtering parameters, are defined as part of Stage 2.

TASK 6. DEVELOPMENT OF AI INTERFACE

This research focused on track geometry issues in the vertical and horizontal planes, which could be addressed by an IMU at the hy-rail wheel. No linear measurements are supported in this version, and as such, gage and lateral alignment are not addressed. Specifically, running surface (or profile), cross-level, and degree of curvature were evaluated. Derived channels that can be computed are super elevation, twist, and warp. Two approaches were evaluated including machine learning and deterministic.

Machine Learning Approach

Upon aligning the IMU data with the ground truth data, this task involves selecting a suitable machine learning model. Given the inherently nonlinear relationship between IMU data and ground truth, the initial choice was Convolutional Neural Networks (CNNs), well-known for their efficacy in learning nonlinear relationships. The following is a summary of the steps for the initial AI interface training, validation, and observations made.

This portion of the research was conducted utilizing the following precursory steps:

> *Data Collection and Preprocessing:* Sensor data related to track geometry parameters was as collected during the initial stages. This data underwent preprocessing steps such as filtration and alignment with ground truth parameters to ensure its quality and relevance, as discussed in the previous section. The final filtering of the sensor data was a frequency-based band pass filter.
>
> *Choice of Model:* After careful consideration, a Convolutional Neural Network (CNN) for the prediction task was implemented. CNNs are well-suited for processing sequential data and have shown promising results in similar tasks. [5]
>
> *Feature Engineering:* In this phase, feature engineering was performed to extract relevant information from the sensor data. Instead of using the original IMU data, computed statistics (minimum, maximum, and mean) for each data sample were utilized, resulting in an 18-dimensional feature vector representing acceleration and rotation along different axes. This would also reduce the complexity of the problem. Initially, only the data from the driver-side sensor was used to predict the left surface, degree of the curve, and cross-level.
>
> *Windowing Strategy:* A windowing strategy was employed to capture temporal dependencies and context in the data. Rather than using a one-foot window, the window size was expanded to the five feet surrounding the ground truth sample. Thus, sensor input from plus/minus two feet served as the input to the CNN, with the TG data serving as the ground truth. This allowed us to combine multiple data samples and choose the corresponding middle-ground truth label for training.
>
> *Model Architecture:* A simple CNN architecture comprising two convolutional layers for the initial training was designed. The first layer had 64 kernels, followed by a pooling layer with a kernel size of 2. The second convolutional layer had 128 kernels, followed by a pooling layer with the same kernel size.

Training and validation for the model was performed recursively. The following steps were conducted during this task of the research:

Data Splitting: To train and evaluate the model, the dataset was partitioned into three subsets: training, validation, and testing. 80% of the total data was allocated for training purposes. The remaining 20% was divided equally, with 10% used for validation and the remaining 10% for testing.

Loss Function and Optimizer: The Mean Squared Error (MSE) loss function was initially selected to train the model. The MSE loss is defined as the average of the squared differences between the predicted (machine learning result) and actual values (measured track geometry data). This loss function is commonly used for regression tasks. In the formula below, y_i denotes actual output and $\tilde{y}_i$ denotes predicted output, and *n* is the total number of points under consideration.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$$

Optimizer Selection: The Adam optimizer was chosen with a learning rate of 0.001. Adam optimizer is an adaptive learning rate optimization algorithm that is well-suited for training deep neural networks. The chosen learning rate helps in controlling the step size during optimization to ensure convergence.

Training Details: The training process involved iterating over the dataset for multiple epochs, or iterations of the complete dataset. The model was trained for a total of 200 epochs, with each epoch consisting of forward and backward passes through the network. The dataset comprised approximately 3000 data samples.

Initial Results: The first iteration of the model showed promising results. The total loss obtained after training was 11%, indicating that the model was able to capture the underlying patterns in the data effectively. **FIGURE 11** shows the prediction from the ML model with the ground truth on the validation data set (approximately 300 feet) for surface, degree of curvature and crosslevel. Observationally, this figure shows the model capturing the underlying trends in the data, however the variation is not quite captured.

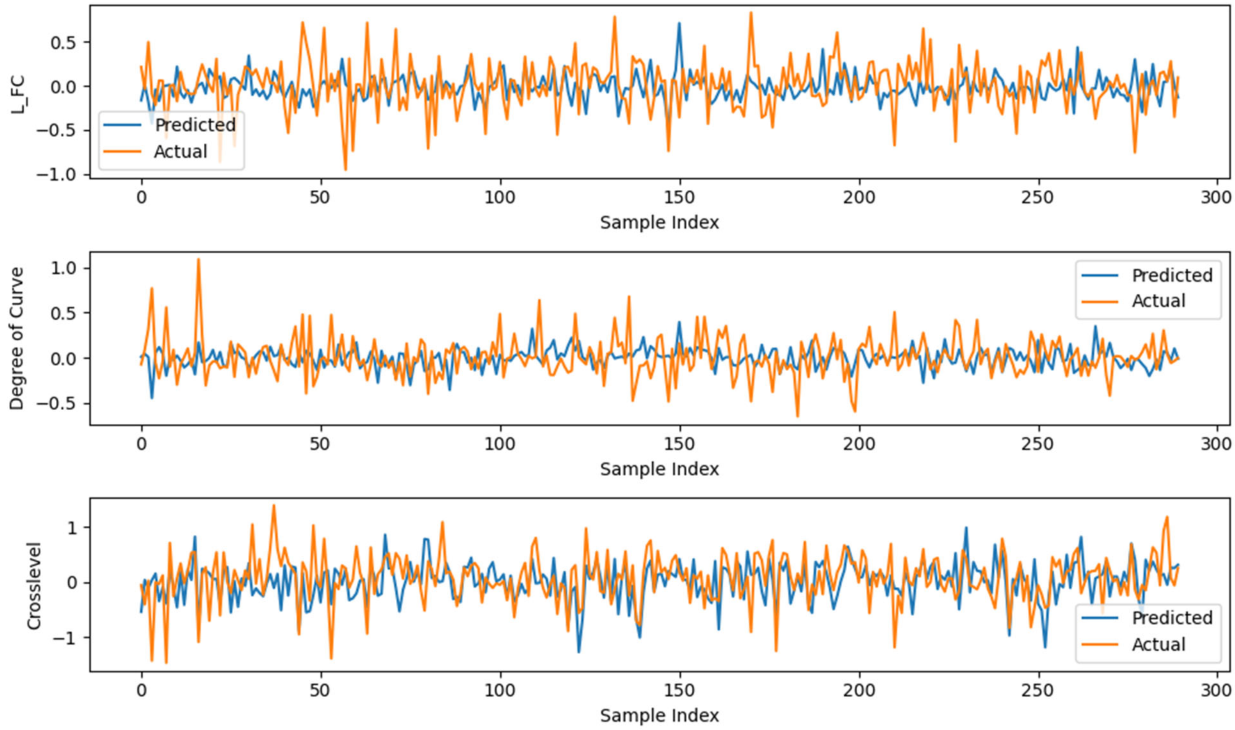


FIGURE 11. First iteration model comparative results for Surface, Degree of Curvature and Crosslevel using MSE loss function

Loss Function Modification: Initially, the Mean Squared Error (MSE) loss function was employed, which calculates the average of the squared differences between the predicted and actual values. However, since the variation of the data showed spikes in the output, which is the actual area of concern, the loss function was modified. MSE loss function penalizes all the data points equally, which may not be suitable for this task. The loss function was changed to the Mean Absolute Error (MAE) loss function, which penalizes the outliers (or spikes) more. MAE calculates the average of the absolute differences between the predicted and actual values. The expression of MAE is given below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \tilde{y}_i|$$

Unlike MSE, MAE penalizes outliers more severely, making it suitable for datasets with significant variations. **FIGURE 12** shows a comparison of the second iteration model predictions with the ground truth results.

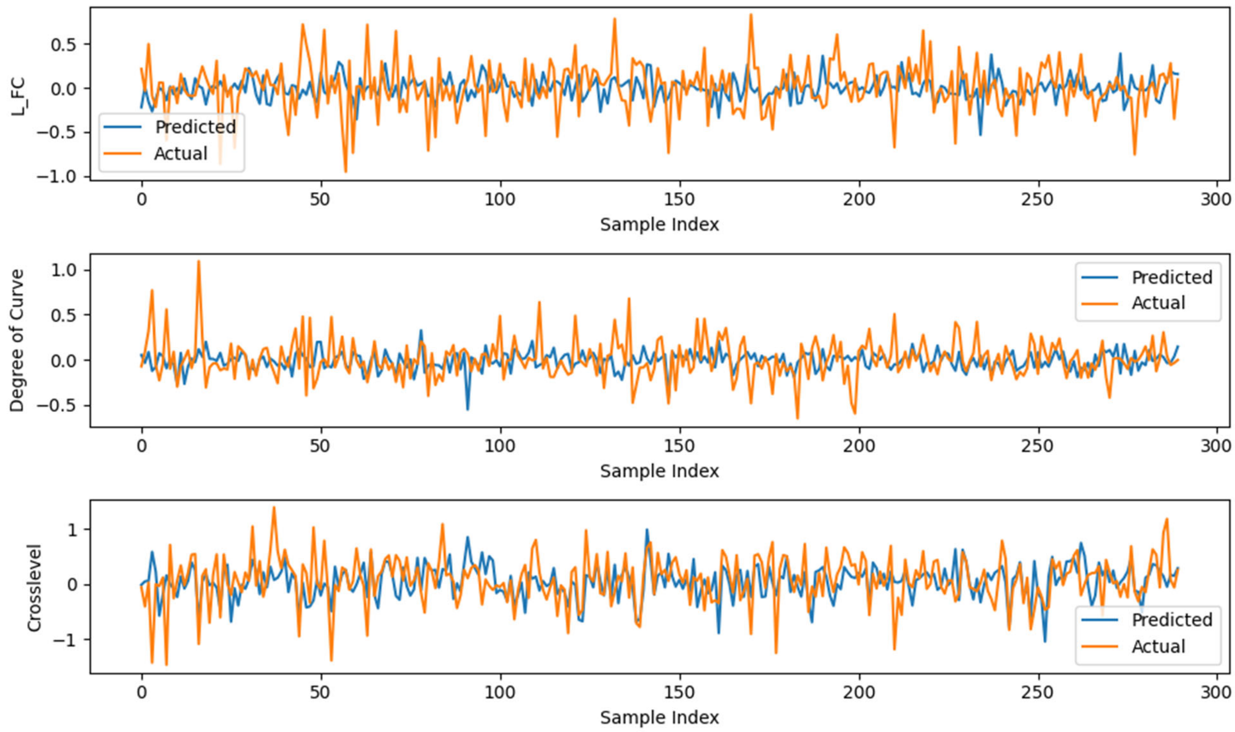


FIGURE 12. Second iteration model comparative results for Surface, Degree of Curvature and Crosslevel using MAE loss function

While the MAE loss function predicted some spikes in the output, it also led to overfitting. The net loss increased from 11% to 23.8%, indicating that the model struggled to generalize to unseen data and was potentially fitting too closely to the training data.

In order to avoid overfitting, L2 regularization and dropout regularization techniques were applied. L2 regularization adds a penalty term to the loss function, which discourages large weights in the model. Dropout regularization randomly drops a fraction of the neurons during training, which helps prevent co-adaptation of neurons and improves generalization. L2 regularization can be achieved by adding weight decay to the optimizer for a convolutional neural network. This adds a penalty term proportional to the squared magnitude of the weights to the loss function. Dropout regularization can be implemented by adding dropout layers after convolutional layers or fully connected layers in the model architecture.

After implementing the regularization, the net error was reduced to 22.6%, and the comparative results are shown in **FIGURE 13**.

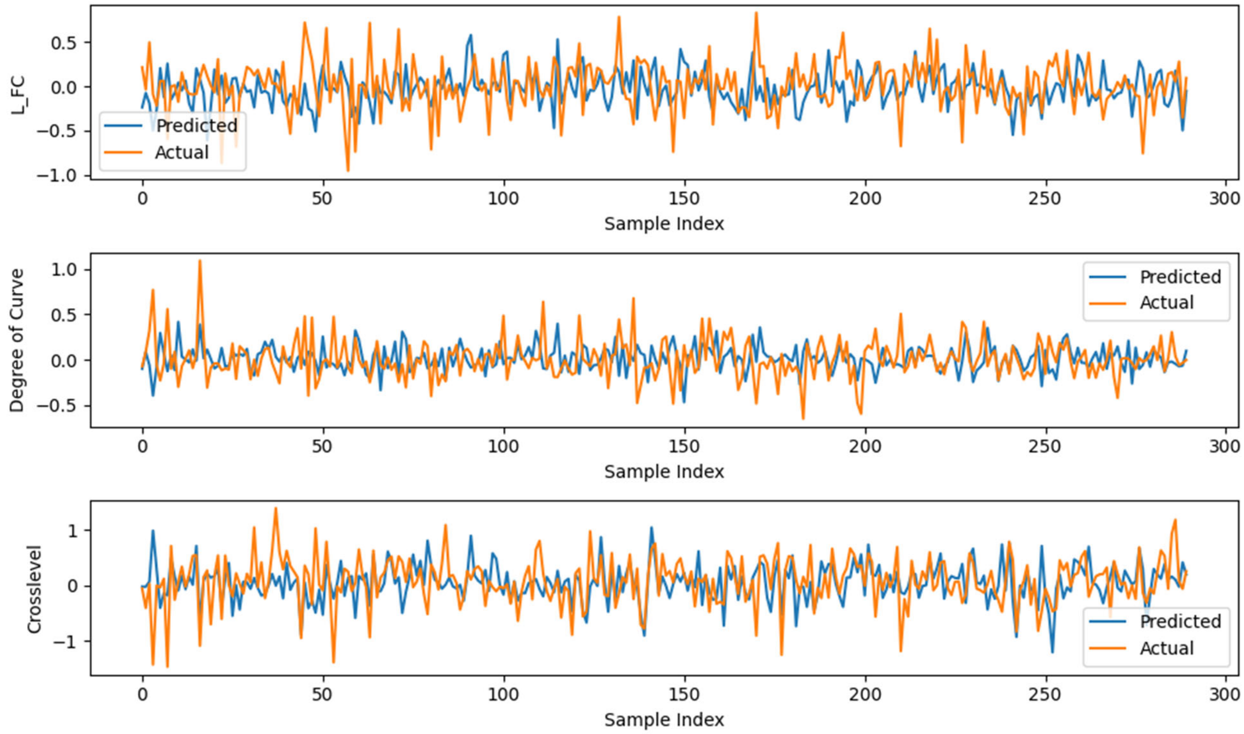


FIGURE 13. Third iteration model comparative results for Surface, Degree of Curvature and Crosslevel after implementing regularization

It must be noted that in the above comparison figures, the 300 feet of data is not contiguous. The ML approach captures points at random for training, validation and testing. Thus, the testing data is approximately 300 feet of random data points within the 7000 feet of data and displayed in a linear format for observational purposes.

Deterministic Approach

The deterministic approach addresses the kinematic outputs of the sensors, specifically, the three axes of acceleration and three axes of rotational velocity. Similar to navigation, Euler angles can be determined for the sensor frame of reference relative to Earth. There are limitations to this approach, requiring a relative reference frame.

To demonstrate this approach, consider cross level, which is defined as the inclination of one rail relative to another, perpendicular to the running axis of the track. **FIGURE 14** shows the reference frame associated with the track, the IMU and Earth. Thus, the gravity vector projection in the transverse plane can be used to define the static angle of inclination (θ_S) of one rail to another according to:

$$\theta_S = ATAN\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}}\right)$$

Knowing this angle, cross level (XL) can be calculated as follows:

$$XL = 59 * \theta$$

However, since the vehicle (and IMU) is in motion, the IMU records other forces such as vibration (acceleration "noise") and centrifugal acceleration. Thus, the static angle determined above can be corrected using the dynamic roll angle, which can be determined from the angular velocity around the *x*-axis through integration. The longitudinal velocity of the vehicle was recorded by the geometry system and associated with the sensor data. when the sensor time-based data was converted to the distance domain, velocity was used to calculate the time traveled between feet of data collected (Δt). The dynamic roll angle (θ_D) is determined from the measured roll angle (w_x) as follows:

$$\theta_{D_i} = \theta_{D_{i-1}} + w_{x_i} * \Delta t_i$$

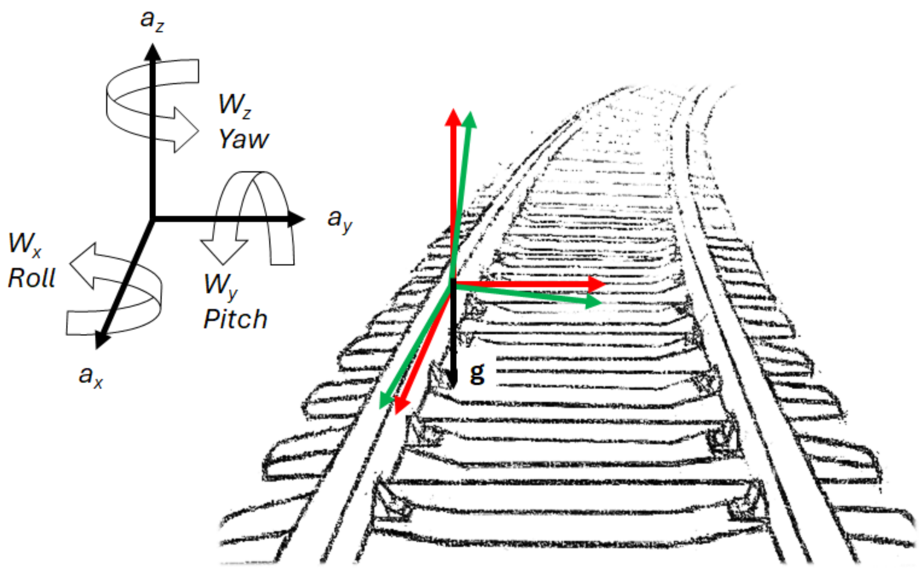


FIGURE 14. Reference frame schematic

Accelerometers pick up vibration which is classified as high frequency noise associated with short term changes. Thus, the accelerometer data is low pass filtered to retain the long-term variations and filter out the short-term variations. IMU's are effective at measuring long term variations, thus the IMU angular velocity data is high pass filtered to attenuate the low frequency aspects of the data and allow the high frequency aspects to pass through. Combining the to portions of the signal results in the filtered roll angle. However, integration of the IMU data results in a cascading error know as drift. To handle this, a complimentary filter can be employed. This is know as data fusion, and several techniques can be employed. [6]

The equation for the low pass filtered static roll angle ($\hat{\theta}_S$) is calculated as follows:

$$\hat{\theta}_{S_i} = \alpha\theta_{S_i} + (1 - \alpha)\hat{\theta}_{S_{i-1}}$$

The equation for the high pass filtered dynamic roll angle ($\hat{\theta}_D$) is calculated as follows:

$$\hat{\theta}_{D_i} = (1 - \alpha)\theta_{D_i} + \alpha\hat{\theta}_{D_{i-1}}$$

The combined roll angle ($\hat{\theta}_i$) becomes:

$$\hat{\theta}_{i} = (1 - \alpha)\hat{\theta}_{S_i} + \alpha\hat{\theta}_{D_i}$$

The cross level at each foot then becomes:

$$XL_i = 59 * \hat{\theta}_i$$

Application of this process to a subset of data is shown in **FIGURE 15**.

The top plot show the raw and low pass filtered roll angle derived from the acceleration signal and the middle plot shows the high pass filtered roll angle derived from the angular velocity signal (note the drift associated with integration). The bottom plot shows a comparison of the cross level from the deterministic approach and the ground truth from the track geometry system. Note that this data is contiguous unlike the randomly selected data used to test the ML model.

The deterministic approach clearly shows the general trend of cross level though there are some locations showing some significant variation. It is expected that this may be due to the data acquisition phase of the project, whereby alignment of disparate data sources resulted in some offset and potentially inaccurate calculations of time between samples of data, which significantly influences the integration step.

A similar approach can be used for surface as shown in **FIGURE 16**, using the appropriate accelerations and pitch angular velocity. In addition, the space curve (*SC*) data is converted to a mid-chord offset (*MCO*) for comparison by digitally imposing a 62' chord on the space curve data according to:

$$MCO_i = \frac{(SC_{i-31} + SC_{i+31})}{2} - SC_i$$

General tendencies and variations are picked up in the determination of surface, with some locations of discrepancy as shown in **FIGURE 16**.

Curvature cannot use the same exact approach since the gravity vector cannot be used to determine yaw. Thus, only the angular velocity about the *z*-axis can be used to determine a relative yaw angle, using integration and mean removing the associated drift. The results are shown in **FIGURE 17**. Good agreement can be seen between the deterministic approach and the ground truth.

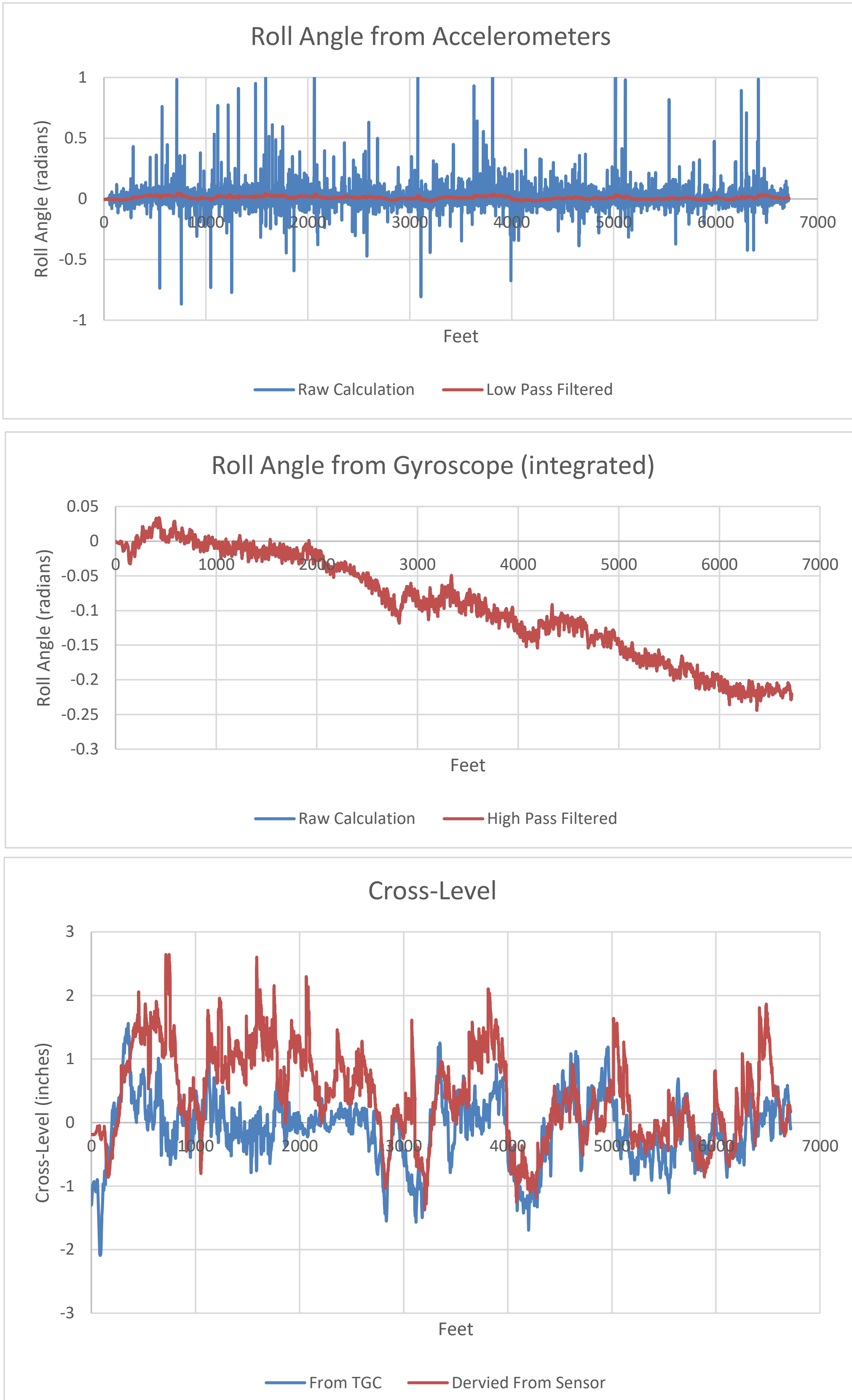
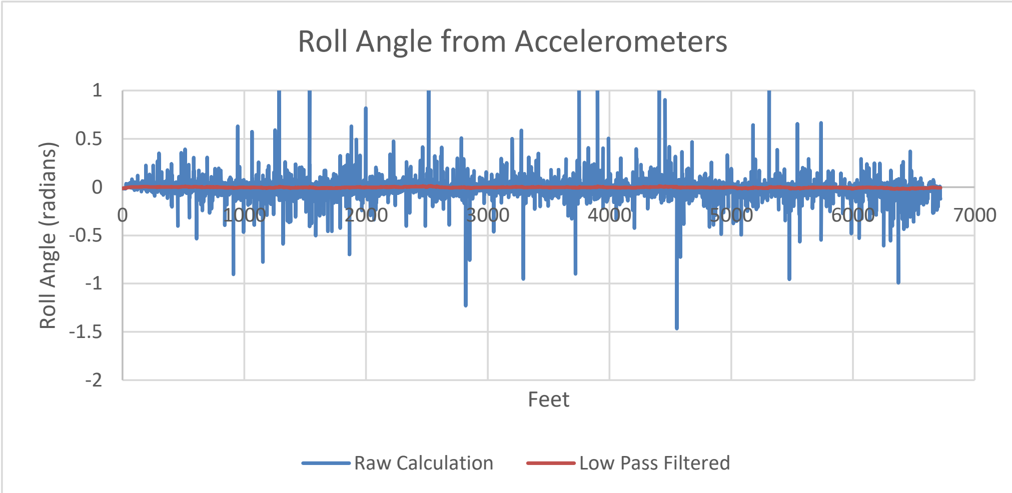
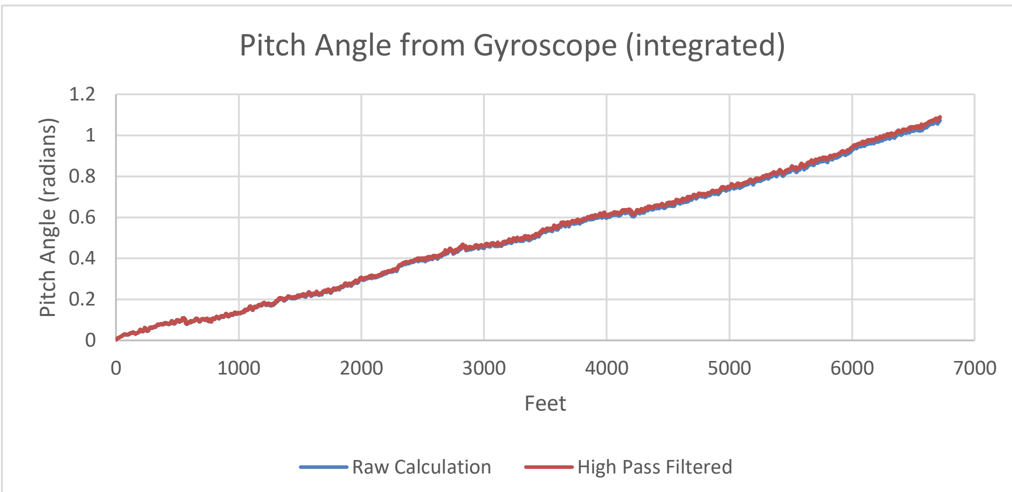


FIGURE 15. Deterministic approach to cross level





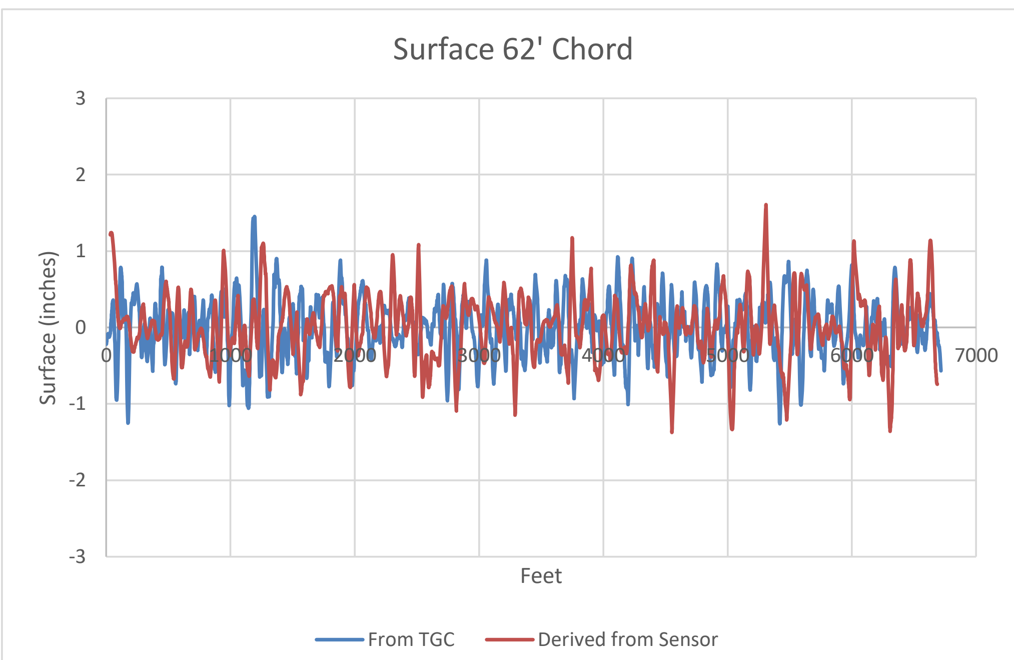


FIGURE 16. Deterministic approach to surface

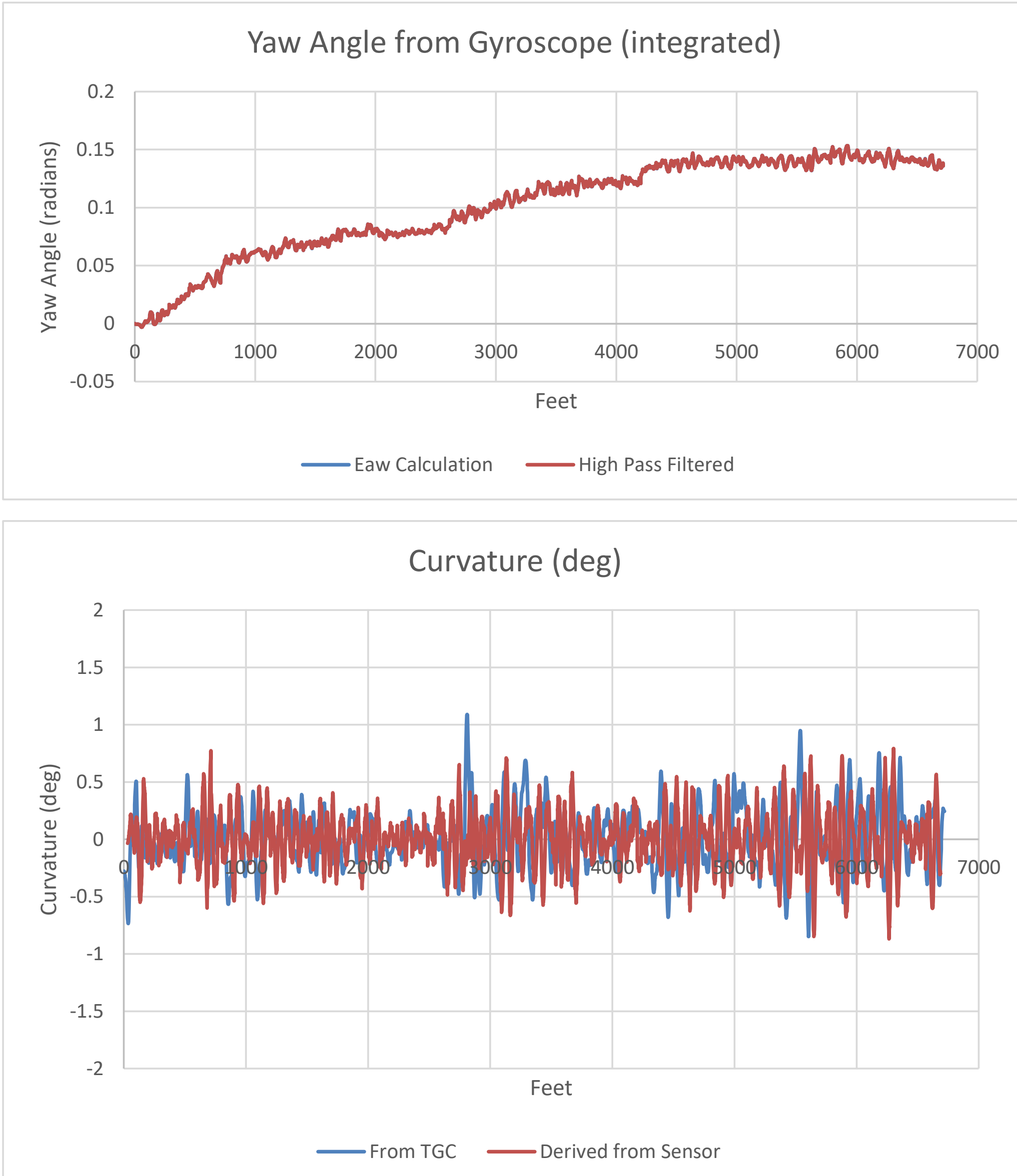


FIGURE 17. Deterministic approach to curvature

TASK 7. PRELIMINARY VALIDATION

From the previous task, observationally, there is agreement between the ground truth and the two approaches used to determine geometry parameters; Machine Learning and Deterministic. However, there are some significant discrepancies in both approaches.

To further validate the data, histograms were created and are presented in **FIGURE 18**. These figures show the distribution of actual points from the track geometry car (TGC) data versus the distribution of predicted points, for both the deterministic (Derived from Sensor) and ML approaches (ML Prediction).

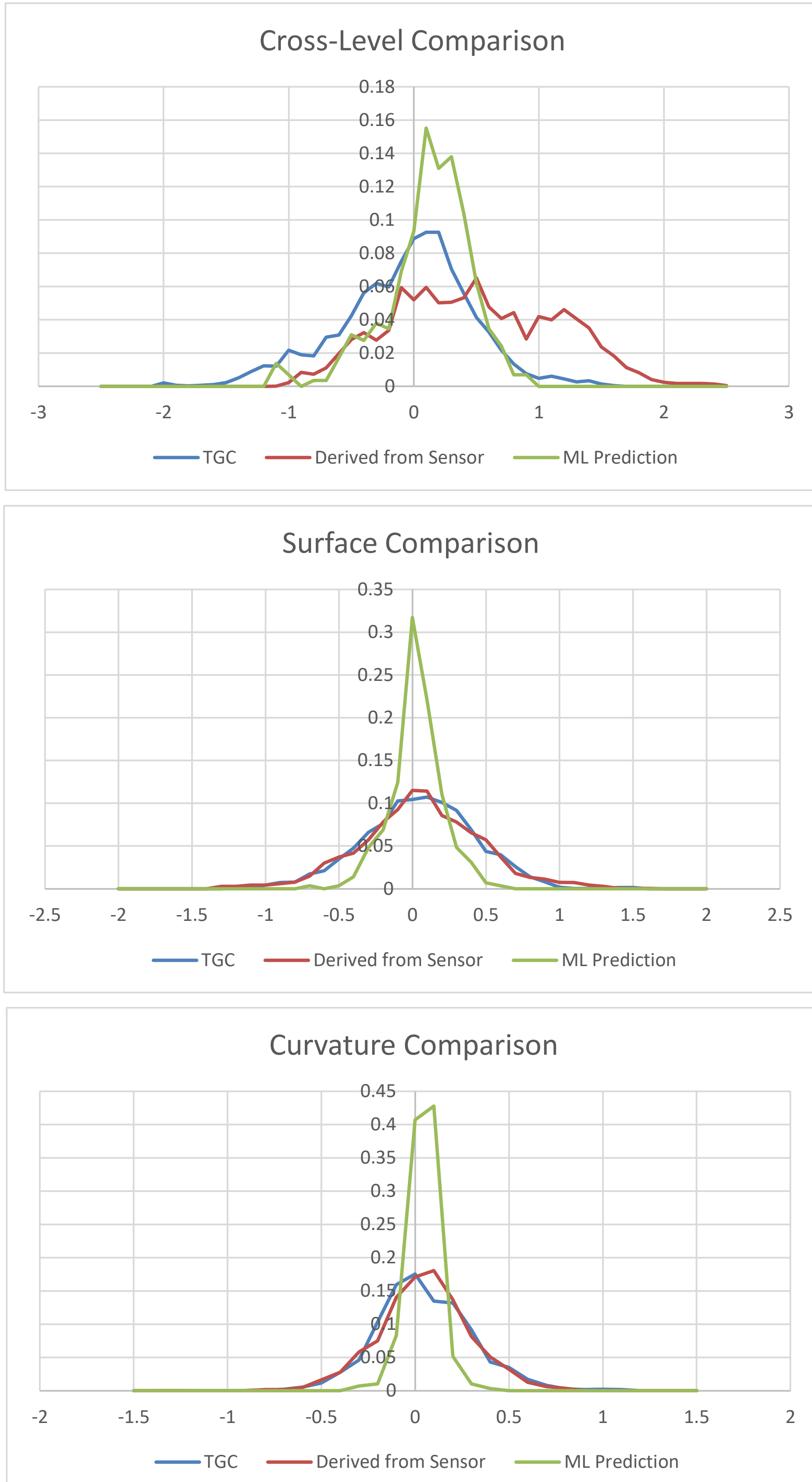


FIGURE 18. Histograms of actual versus predicted values

The top plot of **FIGURE 18** shows the comparison for cross level. The deterministic approach shows a shift to the right, indicating over predicting. This was also evident in **FIGURE 15**. The histogram for the ML prediction was based on the limited test dataset (approximately 100 points), which were collected at random during the testing process. Due to the limited population size and randomness of the data, the distribution analysis is inappropriate. The plots for surface and curvature show excellent agreement for the actual data and the deterministic approaches. This indicates that overall the method is picking up the general trends of the data. Given the ML randomness restriction, histograms were created for ground truth and ML prediction for the 300 point dataset and are provided in **FIGURE 19**. The distributions show that, for the small subset of test data, good agreement is evident, and as supported previously in the comparison graphs.

The distribution analysis allows for an understanding of the general ability to predict the underlying trends in the data. However, observationally, there were obvious discrepancies. To understand this, the root mean squared error was calculated (RMSE), which is defined as the square root of MSE. The RMSE has the same units as the measurement under consideration. The results are shown in TABLE 4.

TABLE 4. Error analysis

Parameter	**Deterministic**	**Machine Learning**
Cross Level	0.83 inches	0.32 inches
Degree of Curvature	0.37 degrees	0.22 degrees
Surface	0.57 inches	0.46 inches

TABLE 4 shows that the machine learning approach is slightly more accurate than the deterministic approach, however, the limited amount of test data limits this conclusion. In addition, overall, the error values are higher than desirable. This again is likely due to the deficiencies in the data acquisition phase.

The system has room for improvement, but the research has shown that the product is technically viable. Improvement concepts will be discussed in the conclusions.

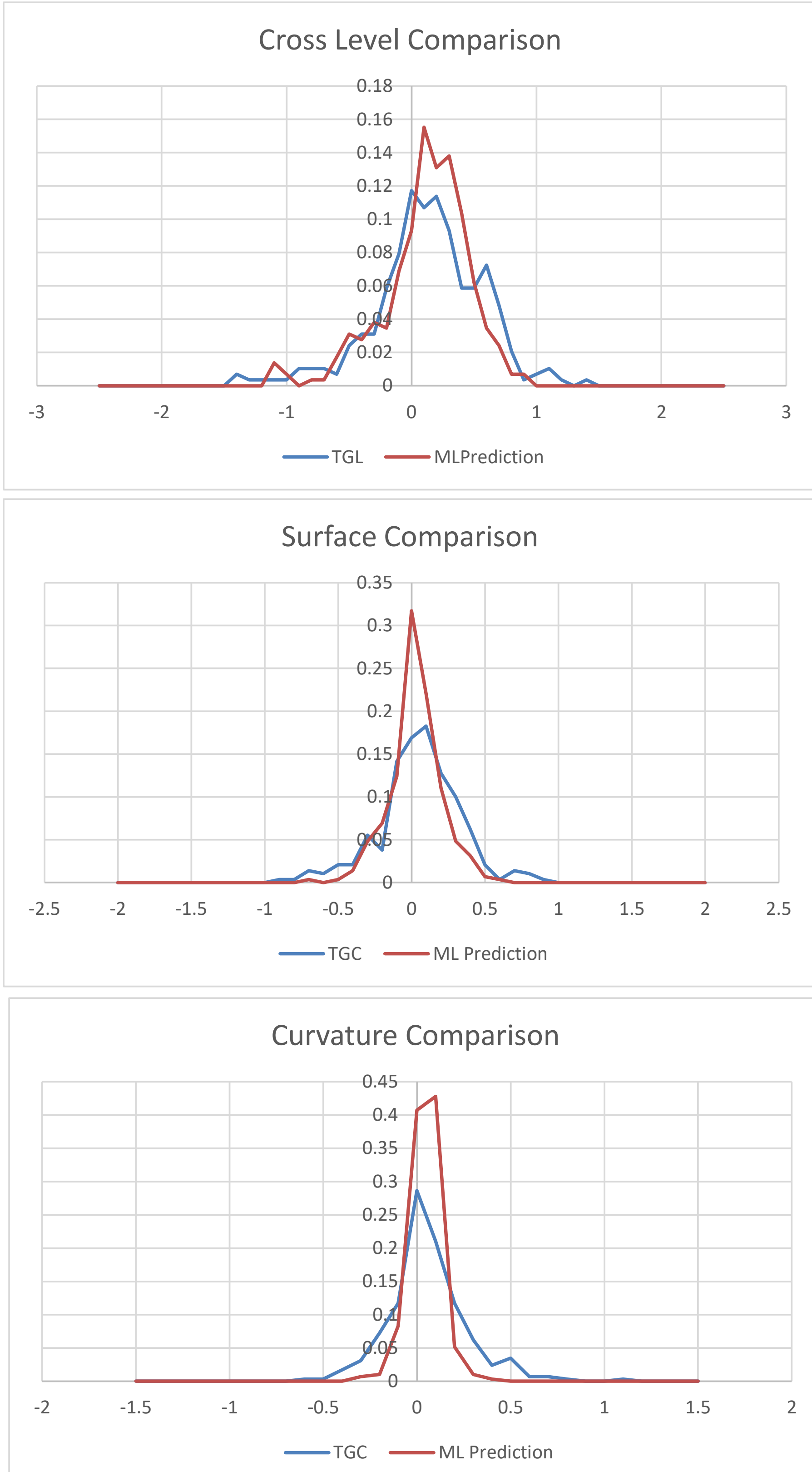


FIGURE 19. Histograms of actual versus ML predictions

TASK 8. PROTOTYPE SPECIFICATION

One of the primary challenges experienced as part of this activity was the data alignment. Due to the nature of the research focusing on the AI interface, a simplified data acquisition approach was required to fit within the scope and budget of this activity. Thus, temporary installation resulted in the sensor data not being consistently aligned with the ground truth data. This can be overcome by linking the sensors directly to the geometry system, which requires an extensive cooperative effort with the geometry system supplier, or connection to a distance measuring device, such as a separate encoder or the electronic control unit (ECU) of the vehicle. Note that this is an envisioned next step in the development process to refine the algorithms. The intent of the SmartWheel is to be independent of a geometry system.

Discussions were held with the sensor supplier to understand the implications of developing a self-contained sensor system that can be deployed practically on a hy-rail vehicle. The following features are required for such a prototype system:

- Secure housing and robust cable connection for the sensor at the hy-rail wheel bearing
    - Adaptable bracketing for securing unit to hy-rail gear
- Tap into speed and distance signal from vehicles ECU
- Incorporate RTK-GPS receiver
- Develop edge computing module
    - Data acquisition
    - Data filtering
    - Data analysis
    - Wi-Fi/Bluetooth data to smart phone for viewing and capture
    - Power from vehicle battery
- Develop application for collecting, displaying and reporting data
    - Phone based
    - Tablet based

FIGURE 20 shows a simplistic block diagram of the potential first-generation prototype. As listed above, the final design for the sensor housing and design of the edge computing module, to include power, processing and communication needs to be accomplished.

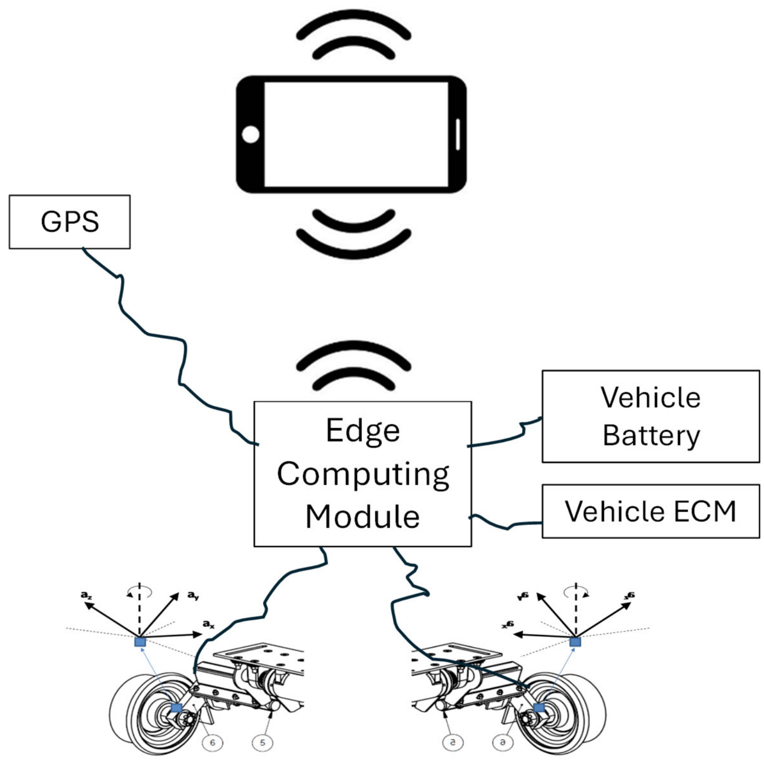


FIGURE 20. Prototype block diagram

PLANS FOR IMPLEMENTATION

As evidenced in the previous section, which will be expanded on in the conclusions, work still needs to be done to develop the first production level prototype. Specifically, the following tasks are defined to extend this research:

1) Develop research level real time software for use on a laptop: One of the major shortcomings of this research was the data acquisition. The first step in formalizing a prototype is to develop in-house data acquisition and analysis software that connects to the vehicle ECM (to get speed and distance signal), connects to a GOS receiver, and connects to and powers the sensors.
2) Design permanent/adjustable bracketry and housing for the sensors.
3) Gather more data on board a hy-rail track geometry car: In order to refine the algorithms developed, additional data is required. Collecting more reliable data will allow for the refinement of the algorithms, including additional filtering as necessary.
4) Design and build edge computing module: Once this is completed, the entire first-generation production prototype will be completed. This can then be tested on the hy-rail track geometry truck, as well as compared to a heavier track geometry car.
5) Consider adding gage and later alignment calculations. (see conclusions for discussion)

Railworks provided the hy-rail track geometry car and is interested in the product and expressed interest in continuing cooperation on this research. In addition, Diversified Metal Fabricators (a hy-rail gear manufacturing company) has also expressed interest in cooperating and have offered to help design permanent bracketry.

The current plan is to solicit additional funding to continue this research and develop arrangement with the identified suppliers.

CONCLUSIONS

The results of the research clearly showed the potential for incorporating low cost electronics in standard equipment used on railroads every day that have the potential to significantly enhance the safety of operations. This research also helped to identify challenges that need to be overcome before a final product can be taken to market.

The combined deterministic and AI approach for algorithm development shows great promise based on the results of this research. Clearly the AI model accuracy needs to be increased; however, the data collected as part of this research has limitations. The research team has identified additional tasks for improving the data collection to finalize the algorithms to be incorporated into a first-generation prototype of the SmartWheel.

One primary take-away from the research is that the increasing technology associated with low-cost MEMs devices offers opportunities for more frequent and autonomous data collection. Incorporating these devices at the hy-rail wheel/rail interface offers the ability to collect data anytime a hy-rail or piece of work equipment is on track. Implemented with the proper communications protocol, anyone with a phone and the app can connect and receive alerts on track condition. The output can also be automatically uploaded to the cloud and continuous monitoring implemented to close the feedback loop and identify changes in condition and/or changing conditions. The key is that this can be accomplished with little investments per vehicle and zero investment for "crowd-sourcing" the data. Realizing this entire system would result in a much safer infrastructure, and potentially minimize other higher cost inspections.

The fundamental results of the research are that the idea shows significant promise with some weaknesses that need to be overcome. Specifically, the research team did not get to a final algorithm due to the nature of the data collected. Additional data collected under a more controlled data acquisition phase that connects both sensors, vehicle speed and GPS would expedite algorithm development to a final conclusion. Also, the research project was focused on the vertical plane of the track and the lateral plane must still be addressed.

One key question from the advisory board is how to economically measure gage, a linear measurement that can not be achieved with an IMU. Currently, gage is measured with laser/optic systems that are very expensive (>25K for just the hardware itself). In addition, contact gage systems are mechanically unreliable. The research team witnessed the contact gage system of the test vehicle derailing quite frequently, requiring the operator to stop the vehicle, disembark, and reseat the system.

The research team was recently involved in using camera arrays and photogrammetric techniques to make linear measurements, specifically for rail wheels, to be published in the near future as an SBOR Phase 1 report. The research team believes an inexpensive gage measuring system can be developed that completes this system to include gage and lateral alignment.

Developing an inexpensive, photogrammetry-based method for measuring track gage can be achieved by placing a set of cameras over each rail. Those cameras will be firmly fixed with respect to each other, i.e. distance between the camera arrays is constant and known. Each camera set will determine the path of the current gage point in separate camera spaces. Fixing the camera sets relative to each other will allow the paths of the gage points for each camera set to be placed in the same coordinate system, which will allow for the calculation of gage. **FIGURE 21** illustrates the idea.

The fundamental technology to be used will either be simple consumer cameras like those used in cell phones or those used in a computer optical mouse. In either case, the cost of the cameras will be on the order of \$10 each. The minimal number of cameras required per set is one. That is possible because a proper spread of images can be created by taking them rapidly enough that proper optimal overlap of the images is achieved. Thus, the cost of the foundational measurement technology could be as low as \$20. Additional redundant cameras will likely be used due to the low cost.

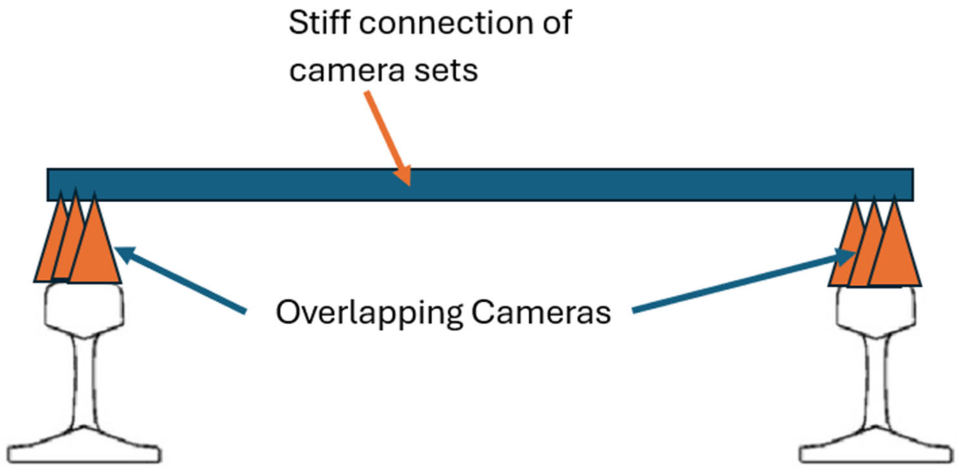


FIGURE 21. Photogrammetric approach to measuring gage

To determine the gauge point, features that are referred to as keypoints, will be found in each image. Each keypoint has an associated descriptor. Descriptors are used to determine the likelihood that a keypoint in one image is associated with the same actual physical location as the keypoint in another image. These matches are used by photogrammetry algorithms to determine the distance from the camera to each keypoint. The other two dimensions are already contained in the image. Thus, the 3D position of each feature can be determined. From these 3D positions, the profile of the rail can be determined and the gauge points extracted.

The processing time for finding keypoints (along with their descriptors) and turning them into 3D information, increases with the resolution of the images. The accuracy of the measurements also increases with the resolution of the images. There are two main methods that should be investigated. One is to see how quickly the high resolution images from a normal cell phone camera can be processed, the other is to determine what sort of accuracy can be gathered by using the cameras used in optical computer mice. The first one promises the highest accuracy (with possibly an undesirable delay), the second one promises real-time processing with possibly inadequate accuracy.

Incorporating a camera array into the hy-rail gear could provide gage and lateral alignment at a low final product cost.

The path to developing and implementing a product in the industry includes the steps outlined in PLANS FOR IMPLEMETATION as well as incorporating the gage and lateral alignment. Once this prototype is complete, rigorous testing must be undertaken to ensure reliability, as well as accuracy. The research team is quite familiar with products taken to market too quickly, with poor demonstration and significant loss of credibility. Thus, the research team intends to solicit funding to generate the next level prototype. Based on the finding therein, the team looks to partner with the previously identified manufacturers and suppliers to develop an arrangement for taking the product to market. The research team has numerous industry contacts and credibility in inspection system development that can open doors for appropriate presentations to potential customers. Customers include all railways, from the Class 1's that need to supplement inspection and locate areas requiring maintenance to the short lines that cannot afford expensive inspection technology, and every railway in between. The ability to increase safety with a low-cost investment is always appealing.

INVESTIGATORS' PROFILES

Dr. Joseph W. Palese is currently Research Assistant Professor at the University of Delaware (UD). He joined UD in 2017 as a Senior Scientist after a 28-year career in the railway industry. Throughout his career Dr. Palese has focused his research and application efforts on obtaining inspection data to aid in enhanced safety and railway track maintenance planning. He has three patents in this area and has developed gage restraint systems, tie inspection systems, track geometry inspection systems, as well as several other inspection components. Using this data he has developed a multitude of degradation analysis and life forecasting software packages, to include rail wear, rail fatigue, tie failure, surfacing/undercutting, rail grinding planning, tie replacement strategies, etc. In the past decade Dr. Palese has been at the forefront of utilizing artificial intelligence for fusing and correlating disparate data sources to determine effects of track component condition on accelerated failure and increased maintenance

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APPENDIX: RESEARCH RESULTS

Sidebar Info

Program Steering Committee: Rail Safety IDEA Program
Month and Year: August, 2024
Title: Development of a Prototype Smart Hy-Rail Wheel
Project Number: SAFETY-49
Start Date: October. 2022
End Date: August, 2024
Product Category:
Principle Investigator:

Joseph W. Palese, PhD, PE
Research Assistant Professor
University of Delaware
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Title/Subhead

Development of a Prototype Smart Hy-Rail Wheel
Low-cost inertial measurement unit provide track inspectors with up to data track condition assessments.

WHAT WAS THE NEED?

The Federal Railway Administration track safety standards require rigorous visual inspections of tracks based on their operating speed (FRA track class), as frequently as twice per week. Often these inspections are carried out using hy-rail (highway/rail) vehicles, with the trained inspector using a set of hand tools (track level, string line, gauges, etc.) to further measure locations that appear to be out of compliance. In addition, railways perform specific inspections using hy-rail or rail bound equipment to measure track geometry, internal rail condition, track strength, tie condition, ballast condition, joint bar condition, etc. These vehicles are expensive to build, maintain and operate. A need exists for a low-cost alternative to assist inspectors in their daily requirements that is accurate and easy to use.

WHAT WAS OUR GOAL?

The objective of this research was to develop a prototype, low-cost, "smart" hy-rail wheel (SmartWheel) to be deployed on an inspector's hy-rail vehicle (or any hy-rail vehicle the railway operates) that assists the trained inspector in identifying locations in track with certain classes of potential defects, in an autonomous and passive manner. It is intended that the SmartWheel be self-contained, autonomous, and provide alerts to the operator. Additionally, the SmartWheel must be inexpensive to implement and provide additional information to the inspector to assist in assessing particular elements of the track condition.

WHAT DID WE DO?

To achieve the research goal, data was collected from identified low-cost IMU sensors temporarily installed on the left and right guide wheels of a hy-rail vehicle that was also outfitted with a comprehensive track geometry measurement system. In this way vehicle response data in the form of triaxial acceleration and angular velocity was collected from each sensor in the time domain, and the actual track condition data was collected by the geometry system in the spatial domain. The IMU sensor data was filtered and used to develop AI and deterministic prediction models for a subset of track geometry parameters including surface, cross-level and curvature.

The AI model consisted of a multi-layer convolutional neural network, trained using a 5 foot input window of sensor data, corresponding to a 1 foot measure of track geometry data. The data was portioned randomly with 80% for training, 10% for testing and 10% reserved for validation. The deterministic model was developed using data fusion of the acceleration and angular velocity signals of the IMU. This approach isolates the low frequency response of the acceleration signal and high frequency response of the angular velocity using integration and a complimentary filter to extract the pertinent geometric parameters used to define track geometry.

These models were then evaluated using a portion of the data not used during training of the machine learning models.

WHAT WAS THE OUTCOME?

The outcome of the research was a viable prediction algorithm for a subset of track geometry parameters using a low-cost IMU. The error of the developed system was approximately 22%, which related to +/- 0.16” to +/- 0.25” of accuracy. This error is larger than desired, however with additional data and further training of the models, it is fully expected that the error can be reduced significantly. This could be achieved with a field deployable prototype.

Only a subset of track geometry parameters were targeted. Specifically, parameters associated with the vertical plane of the track, as well as curvature were investigated. Lateral parameters such as alignment and gage require additional sensors that could easily be integrated with the current SmartWheel design.

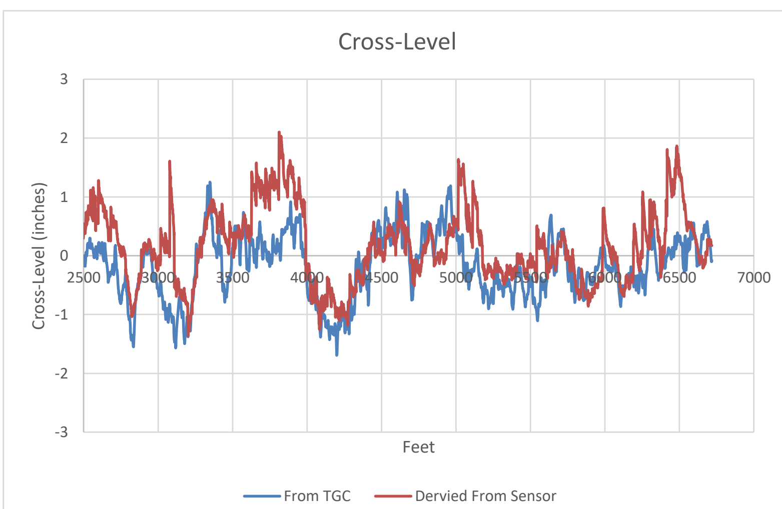
WHAT IS THE BENEFIT?

The primary benefit of this product is a safer operating environment through the low-cost implementation of a tool that assists inspectors in an autonomous fashion in locating potential track defects. A secondary benefit is identifying locations with habitual problems where revised maintenance practices can increase safety and reduce overall costs. Lastly, successful implementation of this research will help inspectors (particularly less experienced inspectors) identify locations that are sometimes quite difficult to quantify, or even recognize, visually. This includes finding locations requiring remediation identified by stand-alone inspection cars. Not all track anomalies are identifiable through this technology, but a significant number of safety related anomalies are identifiable.

LEARN MORE

ADD LINK TO FINAL REPORT

POTENTIAL FIGURES



Subset of track showing predicted versus actual cross-level

Parameter	Deterministic	Machine Learning
Cross Level	0.83 inches	0.32 inches
Degree of Curvature	0.37 degrees	0.22 degrees
Surface	0.57 inches	0.46 inches

Accuracy comparison of modeling approaches

SmartWheel sensor installed on left and right guide wheels of hy-rail vehicle