Faculty Development Grant Report

Research Title:

Comparative Analysis of Fixed-Length and Dynamic Segmentation for Feature Extraction from Non-Stationary Spatial Data

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January 31, 2025

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Abstract

This research presents a comparative analysis of non-stationary spatial data segmentation techniques such as fixed-length and dynamic segmentation based feature extraction efficiency. The study utilizes 5 miles of railway track geometry data, a non-stationary spatial dataset, to assess the effectiveness of both segmentation approaches. The profile (vertical alignment) of the track geometry is used for this purpose. For fixed-length segmentation, the track data is divided into segments of 264 feet (1/20th of a mile), resulting in approximately 100 segments. Dynamic segmentation is performed using an "l2" model-based change point detection algorithm, which adapts to natural variations in the signal. Key features such as standard deviation, kurtosis, and energy are extracted from both segmentation methods. Performance is evaluated based on multiple criteria, including consistency or signal quality across segments, measured using the variance of the signal-to-noise ratio (SNR), computational efficiency in terms of run-time and memory usage, and the discriminative power of the features for classifying track safety and ride-quality conditions, using statistical tests such as the f-test and Fisher score. Results indicate that, fixed-length segmentation outperforms dynamic segmentation (using change point detection algorithm), with significantly lower run-time (0.2 seconds vs. 306 seconds) and more stable signal power across segments (SNR standard deviation: 0.09 vs. 2.2). Additionally, features from fixed-length segments demonstrate higher discriminative power between track safety and ride quality classes, with higher Fisher scores and f-values showing strong statistical significance ($p < 0.05$).

1. Introduction

1.1. Background

Data segmentation refers to the process of dividing large signals in to small segments for targeted analysis. Breaking the data into meaningful sections help isolate specific events, anomalies, or trends that contribute to better decision-making and more targeted results. This is particularly important in the analysis of non-stationary, spatial signals for localized analysis and more accurate feature extraction. In the context of non-stationary spatial signals such as railroad track geometry data, segmentation, might mean breaking up the railway tracks into sections according to operating features, geographic locations, or track conditions. Segments could be categorized based on track bed conditions, gradient, or curvature. Good segmentation improves overall rail network management by allowing in-depth analysis of individual track segments for focused maintenance and resource allocation. Non-stationarity in the context of spatial data such as railway track geometry refers to the variability of statistical properties along the track length. Jiang et al. highlight that railway tracks can drift from their designed positions, leading to significant changes in track geometry that need to be monitored for effective maintenance. This drift exemplifies the non-stationary nature of the data, as the track's condition evolves over time (Jiang et al., 2017a). The deterioration of track conditions, often exacerbated by frequent train passage and track bed deformation, further illustrates the non-stationary characteristics of the data(Chen et al., 2018).

Studies highlight the influence of analytical segment length on the assessment of track quality. Longer analytical segments can improve precision in track quality assessments through a Zero-crossings segmentation strategy (Dawod & Terdik, 2024). This approach allows for a more refined analysis of track conditions, suggesting that while shorter segments may enhance resolution, longer segments can provide a broader context for understanding track behavior. This duality indicates that the choice of segment length should be tailored to the specific goals of the assessment, balancing detail with overall track performance analysis. Li et al. propose a model that divides continuous track lines into adjacent segments of equal length for health evaluation. Their work illustrates that the segmentation approach can significantly influence the derived health indices, which are crucial for resource allocation and maintenance scheduling (Li et al., 2019).

This aligns with the findings of Offenbacher et al., who discuss the development of various TQIs that integrate multiple geometry parameters, suggesting that the mathematical modeling of these indices is sensitive to the segment lengths used in the analysis (Offenbacher et al., 2020). Another study also reinforces the idea that TQIs, which rely on the standard deviations of measured parameters, are influenced by the segment length (Karunianingrum & Widyastuti, 2020). Their findings indicate that a comprehensive assessment of track quality should consider the segment length to ensure accurate performance indicators.

The two widely applicable types of segmentation are fixed-length and dynamic (or adaptive) segmentations. Fixed-length divides the data into segments of equal size whereas dynamic segmentation divides signals adapts the segmentation to the natural variations in the data. The choice between fixed length and variable length (dynamic) segmentation approaches depends on the type of data to be analyzed and the specific goals of the analysis. Dynamic segmentation offers flexibility that can be advantageous in handling non-stationary data. Studies propose a method that adapts segment lengths based on local signal characteristics, which can lead to more accurate decompositions of signals (Ghoraani & Krishnan, 2012). Jiang et al. propose a new filtering and smoothing algorithm for railway track surveying that utilizes inertial measurement units (IMUs) and odometer data. Their findings suggest that the dynamic nature of railway track conditions necessitates a flexible segmentation approach to accurately monitor track deformations and irregularities (Jiang et al., 2017b). Moreover, Soleimanmeigouni et al. provide a comprehensive review of track geometry degradation and maintenance modeling approaches. They emphasize the importance of considering both fixed and dynamic segmentation methods in predicting track geometry conditions, noting that dynamic segmentation can offer more precise modeling of degradation processes (Chen et al., 2018). This review underscores the need for a flexible approach to segmentation that can adapt to the non-stationary nature of railway track data.

While much of the focus has been on dynamic or variable-length segmentation due to its adaptability to non-stationary data, fixed-length segmentation has shown to provide robust performance in various applications such as voice activity detection (VAD), automatic speech recognition (ASR) and speech translation tasks (Gaido et al., 2021; Kamper et al., 2014). Famili et al. argues, the use of fixed segments simplifies the complexity of data processing by facilitating direct comparisons over time while maintaining spatial integrity (Famili et al., 2019). Other notable studies have advocated for fixed-length segmentation as a robust method in analyzing non-stationary spatial data such as railway track geometry data in some applications. Fixed-length segments provided more consistent results when evaluating track quality indices, suggesting that a uniform segment length can enhance the reliability of feature extraction in spatial datasets (Majstorović et al., 2022). The findings by Zarembski et al. also suggested that consistent data segmentation can lead to better predictive modeling of track geometry exceptions (Zarembski et al., 2017). Gao et al. argue that fixed-length segmentation allows for easier comparison and analysis of mechanical motion curves, thereby facilitating more accurate fault diagnosis in the intelligent diagnosis for railway turnout switches (Gao et al., 2022). In the context of machine learning, Putra et al. also highlight the necessity of fixed-length segments for feature extraction in accelerometer-based fall detection systems. They argue that fixed-length overlapping or non-overlapping sliding windows are essential for effective data segmentation, which can be extrapolated to other domains, including railway track data analysis (Putra et al., 2018). This reinforces the idea that fixed-length segmentation can provide a structured approach to data handling, which is crucial for machine learning applications.

The process of converting unprocessed data into a collection of insightful features appropriate for analysis and modeling is known as feature extraction. In the context of railroad track, the term 'geometry' is concerned with the properties and relations of points, lines, curves and surfaces in the three dimensional positioning of railroad track. The geometry of the track in space is mainly described by parameters such as surface/profile, alignment, gage, cross-level, twist, curvature, superelevetaion and warp (HARSCO Rail, 2020). Profile/Surface (Left/Right) describes the change in elevation of the rail surface in the vertical plane over a track length. Alinement (Left/Right) refers to the layout of the track in the horizontal plane. Gage refers to the distance between the face of the rails at a distance of 5/8" below the top of the rail. The 5/8" value is based on typical contact location of the wheel flange. The nominal gage in North America is 56.5". Cross-level refers to the difference in height between the two adjacent rails at any given point along the track. Twist refers to the algebraic difference of two cross level measurements a defined distance apart, typically 31' or 62'. Warp refers to the algebraic difference of the maximum and minimum cross level measurements within a defined window, typically 31' or 62'.

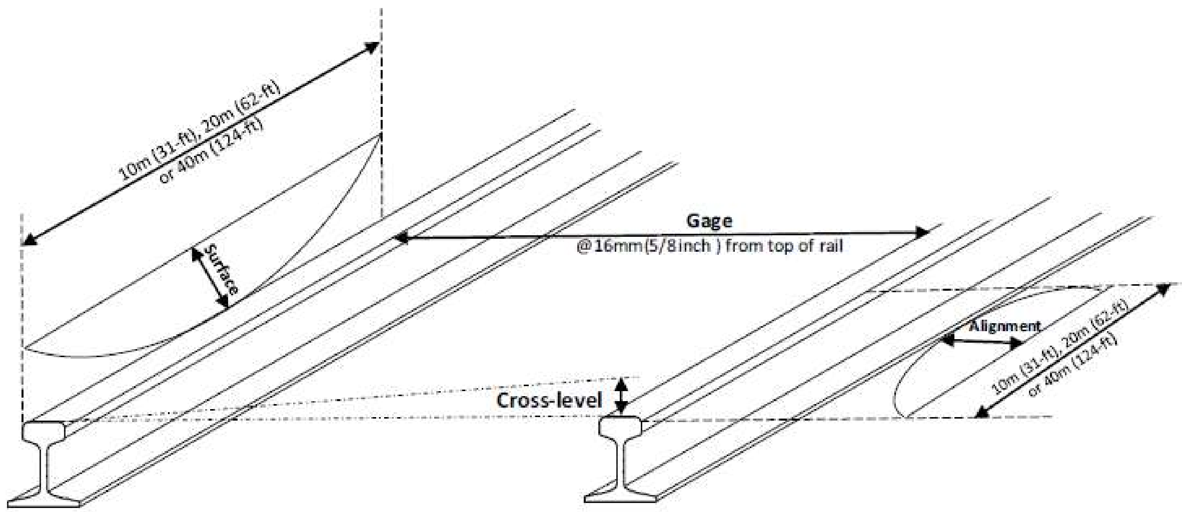

Figure 1: Schematic diagram of track geometry parameters (Lasisi & Attoh-Okine, 2019)

Effective analysis of railroad geometry data is crucial for identifying defects, enabling proactive maintenance planning and ensuring the safety of railway operations. Track geometry defects are among the leading causes of train derailment in the United States. Studies show that geometry defects and broken rail are the leading causes of freight derailments for major US railroads (Liu, 2017). According to the train accident statistics by the Federal Railroad Administration (FRA) over the past 10 years, track failure is one of the leading causes of train derailments in the United States. Figure 2 shows the FRA's number of reported derailments in the US in the last ten years by cause.

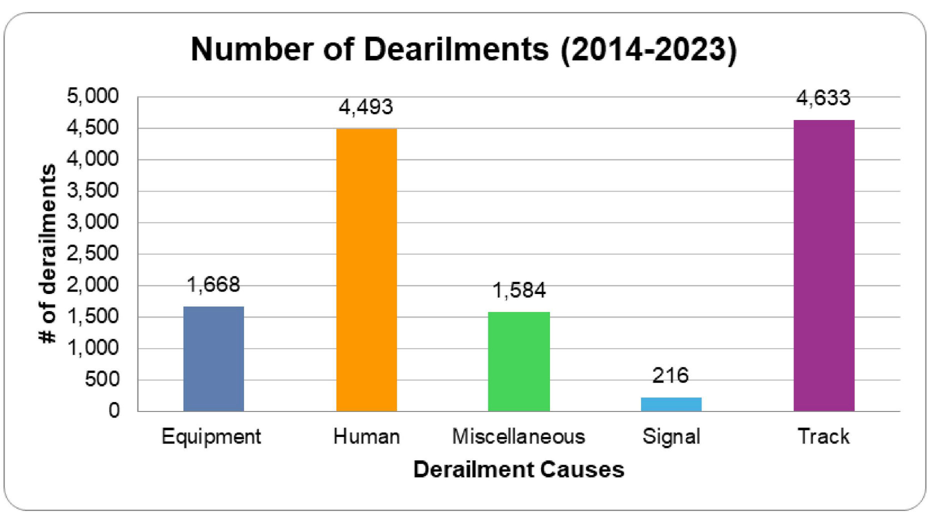

Figure 2: Number of train derailments by cause

When it occurs, train derailment causes significant safety, economic and environmental impact on the public. The economic impact is not only limited to the direct loss incurred due to the damage associated to the derailment itself but also due to the subsequent disruption in operations. In the case of derailment involving HAZMAT trains, the cost can be significantly higher due to the potential long term environmental damage and associated health risks to the public. Recent events in the United States and other parts of the world are good examples (Schnoke et al., 2023). Figure 3 shows that the monetary damage caused by track related train derailments is by far the most consequential compared to the other causes.

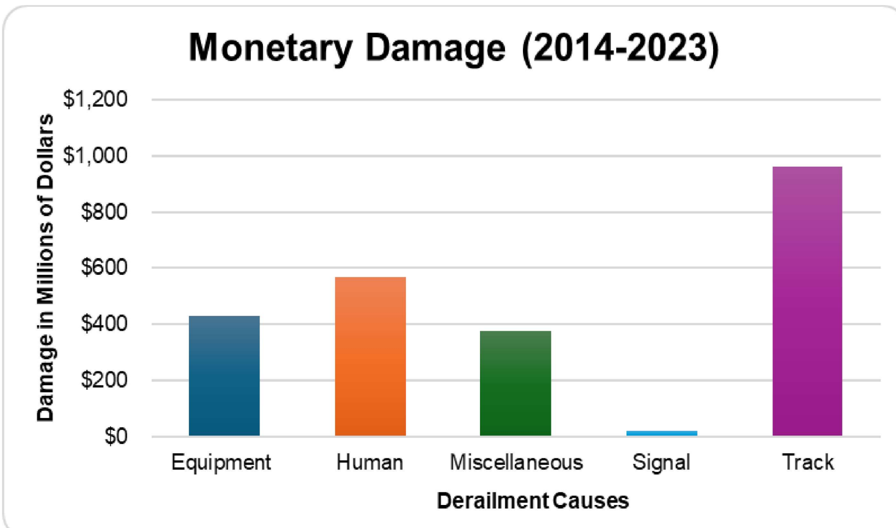

Figure 3: Monetary damage of train derailments by cause

Further analysis of the FRA data revealed, among different track related failures, geometry defects are among the leading causes of train derailment in the United States. Other studies have also established a similar fact that geometry defects and broken rail are the leading causes of freight derailments for major US railroads (Liu, 2017). Figure 4 shows the breakdown of derailment causes in to specific aspects of the track such as road bed defects, track geometry rail & joint defects, turnouts and structures.

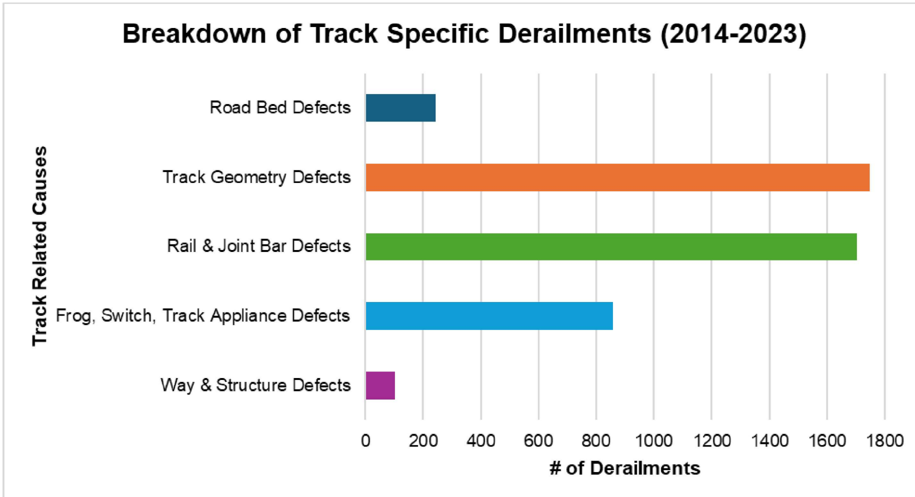

Figure 4: Number of derailments by track related causes

As indicted in Figure 5, about 40% of the track related derailment monitary damages are attributed to geometry defects.

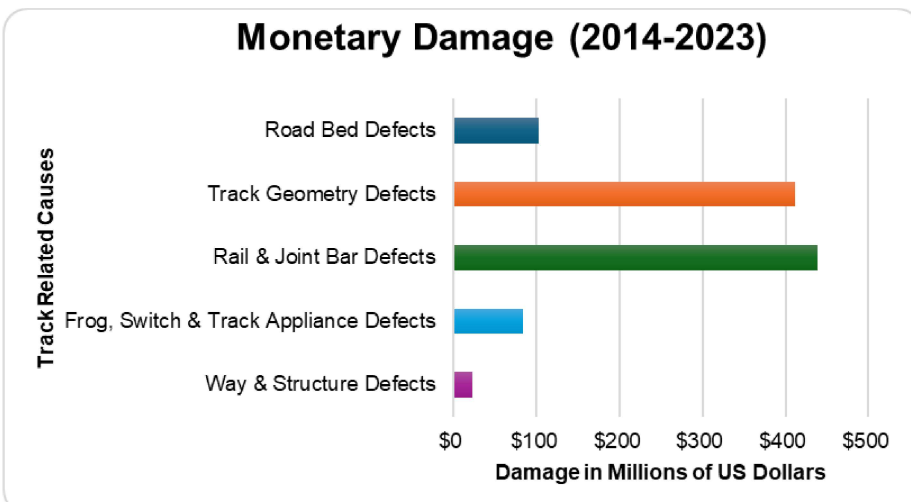

Figure 5: Monetary damage of track related derailments

The trend analysis of the ten years FRA data (Figure 6) shows slight overall decline in the number of track related accidents. However, compared the previous year, track related accidents have shown a 16% increase in 2023 which is a step in the wrong direction.

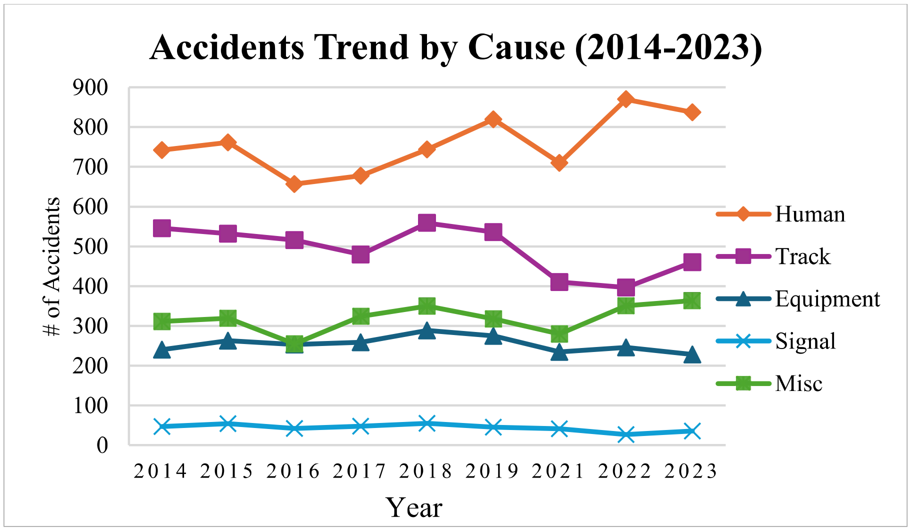

Figure 6: Trend Analysis

As discussed above, with over a $1 Billion lost over the last decade only due to track related causes, there is an urgent need to make railroad tracks safer.

1.2. Motivation and Objective

In the context of signal processing and data analysis, especially pertaining to non-stationary spatial data such as railway track geometry, data segmentation plays a pivotal role in the quality and applicability of the extracted features. Traditional fixed-length segmentation, recognized for its simplicity and ease of implementation, may not fully accommodate the dynamic nature of the data. This method can result in the potential misrepresentation of significant events or anomalies due to its static boundaries. On the other hand, dynamic segmentation, which adjusts to the inherent variability in the data, offers the potential for more precise and contextually relevant insights. However, this method can be complex to implement and may require more computational resources, posing challenges in terms of efficiency and scalability. The comparative efficacy and applicability of these segmentation strategies in handling non-stationary spatial data remain underexplored. This gap underscores a critical need for a systematic evaluation to guide analysts in choosing the most appropriate segmentation method, thereby enhancing the accuracy and effectiveness of subsequent analyses.

The primary objectives of this study is to systematically compare the effectiveness of fixed-length and dynamic segmentation methods in extracting meaningful features from non-stationary spatial data. This includes assessing the quality of features in terms of their ability to capture relevant data characteristics and their utility in subsequent analytical tasks. The study utilizes 5 miles of railway track geometry data, a non-stationary spatial dataset, to assess the effectiveness of both segmentation approaches. In the case of dynamic segmentation, change point detection algorithm based on “l2” model which adapts to natural variations in the signal has been employed.

2. Methodology

2.1. Data Description

This study utilizes five miles of track geometry data obtained from a mainline heavy axle load, Class 4 freight track. The geometry data includes the vertical alignment (profile) of the track, the horizontal alignment, gauge, cross-level and twist. These geometry parameters are key for assessing ride quality and safety conditions of a track. Track geometry data serves as an ideal subject for studying segmentation of non-stationary spatial data due to its intrinsic variability and complex nature. This type of data typically exhibits significant fluctuations over both short and long distances, influenced by factors such as rail wear, environmental conditions, and maintenance practices. The non-stationary characteristics of railway track data where patterns and structural changes occur unpredictably pose unique challenges in signal processing and feature extraction. Applying different segmentation techniques to such data, helps explore and validate methods for effectively capturing critical features that reflect the actual condition of the track, leading to more accurate diagnostics and predictive maintenance strategies. This makes railway track geometry a compelling case study for advancing segmentation methods and improving analytical approaches in handling non-stationary spatial data across various applications.

In addition to track geometry data, ten years of train accident report data (2014–2023) obtained from the FRA’s Office of Safety Analysis was utilized in this research. Analyzing this accident data is crucial for understanding how irregularities in track geometry contribute to train accidents, highlighting the critical role that precise data segmentation plays in identifying and mitigating these risks. This underscores the importance of developing robust approaches for handling non-stationary spatial data. Such approaches ensure that subtle yet critical variations in the track geometry, which could potentially lead to accidents, are accurately captured and addressed, thereby enhancing the safety and reliability of railway operations

2.2.Research Design

This research employs a comparative analysis approach to determine the effectiveness of fixed-length and dynamic segmentation techniques to extract features from non-linear and non-stationary spatial signals. The research is conducted in four key phases: (1) literature survey (2) data pre-processing and exploration, (3) data segmentation and feature extraction (4) performance analysis and comparison. Extensive literature review has been conducted to understand the state-of-the art and identify the gaps in data segmentation and processing. Data pre-processing and exploratory data analysis has been conducted to understand the underlying characteristics of the data. The sample data was segmented using both fixed-length and dynamic segmentation techniques and statistical features such as minimum, maximum, standard deviation, energy, kurtosis and skewness were extracted from segments in both cases. The efficiency of each method was evaluated based on performance metrics such as computational efficiency, signal stability across segments and discriminative power of the features.

2.3. Data Segmentation

2.3.1. Fixed-Length Segmentation

Fixed-length segmentation involves dividing a continuous stream of data into uniform sections for further analysis. By breaking down the data into uniform segments, the risk of information overload is minimized, making the data more manageable for processing and interpretation. A uniform segmentation approach ensures that each segment contains a similar number of observations, simplifying the comparison of track conditions across different sections (Famili et al., 2019). This method is particularly effective when there is a need to apply machine learning algorithms, which benefit from consistent input sizes across training samples.

Mathematically, fixed-length segmentation can be represented as follows: Let the non-stationary spatial signal be represented as, $X = \{x_1, x_2, \dots, x_n\}$, where n is the total number of data points. The signal is divided into m segments of equal length, l, such that: Segment 1: $\{x_1, x_2, \dots, x_l\}$, Segment 2: $\{x_{l+1}, x_{l+2}, \dots, x_{2l}\}$ ... Segment m: $\{x_{(m-1)l+1}, x_{(m-1)l+2}, \dots, x_n\}$ where $m = n/l$, and l is the predefined segment length.

2.3.2. *Dynamic Segmentation*

Dynamic segmentation creates segments of varying lengths to accommodate the data's inherent fluctuation. These deviations are frequently found using change detection methods, such as the "l2" model-based change point detection. The "$l2$" model-based change point detection algorithm is a data-driven approach that adapts the segment lengths based on the local characteristics of the signal (Jaramillo et al., 2021). Let the non-stationary spatial signal be represented as a time series, $X = \{x_1, x_2, \ldots, x_n\}$, where n is the total number of data points. The algorithm seeks to find the optimal set of change points, $k = \{k_1, k_2, \ldots, k_m\}$, where m is the number of change points, such that the following cost function is minimized:

$$C(K) = \sum_{k=1}^{K} \sum_{t=t_{k-1}+1}^{t_k} (x_t - \hat{x}_k)^2 \tag{1}$$

where:

- K is the number of change points.
- $\{t_1, t_2, \ldots, t_K\}$ are the change point positions.
- $\hat{x}_k$ is the mean of the signal in segment k, which is typically estimated as the average of $x_t$values within the segment k.
- t_{k-1} and t_k define the boundaries of each segment.

The algorithm iteratively searches for the optimal set of change points that minimize the overall cost function, adapting the segment lengths based on the local signal characteristics. The "l2" model, which is based on detecting changes in the mean of the signal, is a practical and efficient choice for many applications, particularly when working with large datasets such as track geometry data. Unlike more complex non-linear models such as "rbf," which require substantial computational resources and can run into memory issues, the "l2" model is computationally lightweight. It provides a good trade-off by capturing important changes in the signal without the need for expensive kernel computations or high memory usage. While the "l2" model may not detect highly non-linear changes with the same precision as the "rbf" model, it is often sufficient for detecting significant transitions, making it ideal for real-time applications or large-scale analyses. By leveraging the advantages of dynamic segmentation while maintaining a low computational footprint, the "l2" model strikes a balance between accuracy and efficiency, offering a robust solution without requiring costly resources. The use of the Radial Basis Function “rbf” model is impractical due to the heavy computational demand caused by an attempt to compute a large Gram matrix as part of the RBF kernel. This issue typically arises when the dataset is large, and the Gram matrix (which scales quadratically with the number of data points) becomes too large to fit in memory.

2.4. Feature Extraction

This research attempts to discover whether segmentation techniques offer more dependable and discriminative features for assessing track quality and safety by concentrating on feature extraction from both fixed-length and variable-length segments. Several assets of the signal's unpredictability, dispersion, and strength can be captured by the chosen characteristics, which include energy, kurtosis, and standard deviation. These characteristics are examined to determine how well they capture the track's underlying conditions and how well they serve to highlight locations that might need maintenance or provide safety hazards.

2.4.1. Extreme Values

Extreme values (minimum and maximum), are useful statistical features that can be extracted from non-stationary spatial data, such as railroad track geometry. The minimum value, denoted as x_min, is the smallest value in the dataset. Minimum value can be expressed as: $x_{min} = min\{x_1, x_2, \ldots, x_n\}$. It represents the lowest point or the most extreme low value in the spatial signal. The maximum value, denoted as x_{max}, is the largest value in the dataset. The maximum value can be expressed as: $xmax = max\{x_1, x_2, \ldots, x_n\}$. The maximum value represents the highest point or the most extreme high value in the spatial signal.

2.4.2. Standard Deviation

Standard deviation is a statistical feature that quantifies the amount of variability or dispersion in a set of data values. It indicates how much the individual data points in a dataset deviate from the mean (average) value of the dataset. A higher standard deviation indicates more spread out data, while a lower standard deviation indicates that the data points are closer to the mean.

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{2}$$

Where n represent the total number of data points in the dataset, x_i represents each individual data point and $\bar{x}$ represents the mean of the dataset, calculated as $\bar{x} = \sum_{i=1}^{n} \frac{(x_i - \bar{x})}{n}$

2.4.3. Energy

Energy is the measure that quantifies the total magnitude of a signal or a dataset. It provides a sense of how "strong" or "intense" the signal is over its duration/distance or over the dataset's range.

$$Energy\ (E) = \sum_{n=0}^{N-1} |x[n]|^2 \tag{3}$$

x_i represents the value of the signal at the i^{th} point. N is the total number of points in the signal or dataset. The absolute value squared $|x_i|^2$ ensures that all contributions are positive, emphasizing the magnitude of each point without regard to its direction.

2.4.4. Skewness

Skewness is a statistical measure that describes the asymmetry of the distribution of values in a dataset relative to its mean. It quantifies how much the distribution of the dataset leans to the left or right, providing an indication of the deviation from a normal distribution.

$$Skewness = \frac{N \sum_{i=1}^{N} (x_i - \bar{x})^3}{(N-1)(N-2)s^3} \tag{4}$$

x_i are the individual values in the dataset, $\bar{x}$ is the mean of the dataset, s is the standard deviation, N is the number of data points.

2.4.5. Kurtosis

Kurtosis measures the shape and spread of the decomposed signal. High kurtosis might indicate the presence of transient events or defects. It can also be an indicator for a greater prevalence of tailedess or outliers in the decomposed signals, which can be important for detecting transient events in the signal.

$$Kurtosis = \frac{N}{(N-1)(N-2)} \sum_{i=1}^{N} \left(\frac{x_i - \mu}{\sigma}\right)^4 - 3 \tag{5}$$

where x_i represents each individual data point in the dataset, μ is the mean of the data points and σ is the standard deviation of the data points.

2.5. Scope and Limitation of the study

This study focuses on a comparative analysis between fixed-length and variable-length (dynamic) segmentation techniques applied to non-stationary spatial data. For the fixed-length method, a predefined segment length of $264\ ft\ (1/20^{th}\ of\ a\ mile)$ is utilized, a standard measurement frequently employed in railway track condition assessments and maintenance planning. The choice of this specific length aims to align the study with industry practices, facilitating relevant and actionable insights. On the other hand, the dynamic segmentation approach in this research employs a change point detection algorithm based on the "$l2$" model. This model was selected for its computational efficiency, providing a robust framework for identifying significant changes in the data while managing resource utilization effectively.

While this study provides a thorough comparison of fixed-length and dynamic segmentation methods, it acknowledges certain limitations. The use of the "$l2$" model for dynamic segmentation, while efficient, might not capture as complex changes in data as other models, such as the radial basis function ("rbf"). Therefore, the results might not generalize to scenarios where more sophisticated change point detection is required. Future research could extend this work by exploring the "rbf" model or other advanced dynamic segmentation algorithms. Such investigations could offer a broader understanding of how different segmentation strategies perform across a wider range of non-stationary spatial data scenarios, enhancing the robustness and applicability of the segmentation techniques.

3. Exploratory Data Analysis (EDA)

3.1. Overview

Exploratory data analysis is an approach of analyzing data sets to summarize their main characteristics, often using statistical graphics and other data visualization methods. The core purpose of EDA is understanding the underlying structure of the data set. The key aspects of EDA are identifying patterns and trends, detecting anomalies and outliers and assessing data quality and structure (Nicodemo & Satorra, 2022). In this research, different graphical EDA techniques such as line graphs, histograms, box-plots and correlation heat maps have been applied to the track geometry data.

3.2. Line Graphs

Line graph is a commonly used data visualization method to display information as a serious of data points connected by straight line segments. In the context of railroad track geometry data, the measured geometry parameter is plotted along the track length. Line graph helps to visually identify deviations from the desired alignment, the presence of outliers, trend analysis, identify potential problem areas and comparing different sections of the track side by side to prioritize maintenance based on the severity of deviations. The line plot for mile post 56 indicated in Figure 7 shows some sharp spikes in this track section. Particularly the largest spike around 3000 ft calls for further investigation since the amplitude of this irregularity tops 2 inches which exceeds the FRA safety threshold for class 4 track. This initial observation prompts closer look in to this section of the track to figure out if this is indeed a defect or some sort of outlier.

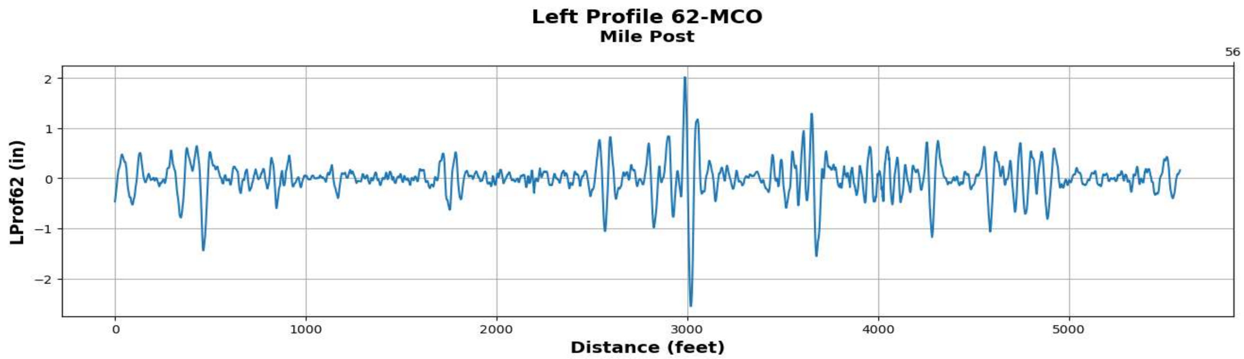

Figure 7: Line graph for Left Profile 62' MP 56

Besides aiding to identify a problem area with in a segment, line plots can also facilitates a visual comparison between different segments of the track. Upon visually inspecting the line plots, the track segment around mile post 56 appears significantly rougher compared to the segment around mile post 58.

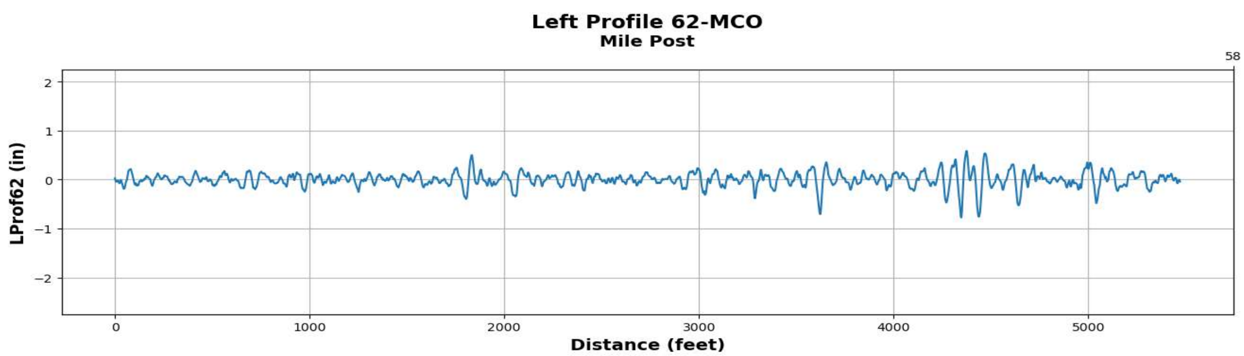

Figure 8: Line graph for Left Profile 62' MP 58

3.3. Box-whiskers Plots

Box-plots visual represent the distribution of the data through five key summary statistics such as the minimum (min), lower quartile $(Q1) = the\ 25^{th} pecentile$, median $m = the\ 50^{th} percentile$, upper quartile$(Q3) = the\ 75^{th} percentile$, and maximum (max). Box-plot is also a powerful tool to identify the presence of outliers in the data. Figure 9 and Figure 10 show the distribution of the data for each geometry parameters in mile posts 56 and 58 respectively. The box-plot at mile post 56 shows a larger distribution range and exceptions compared to mile post 58. This is indicates that the track section around milepost 56 is rougher (larger irregularities) compared to milepost 56 which is consistent with the line plot.

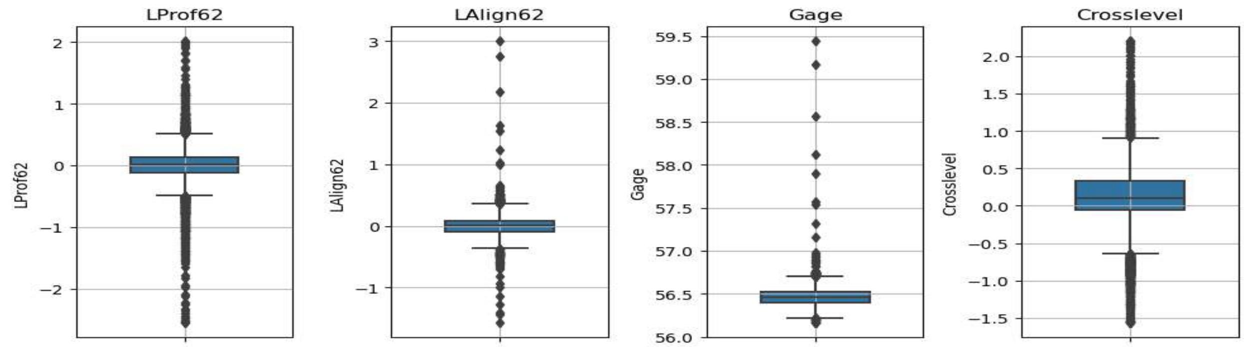

Figure 9: Box and whiskers plot (MP: 56)

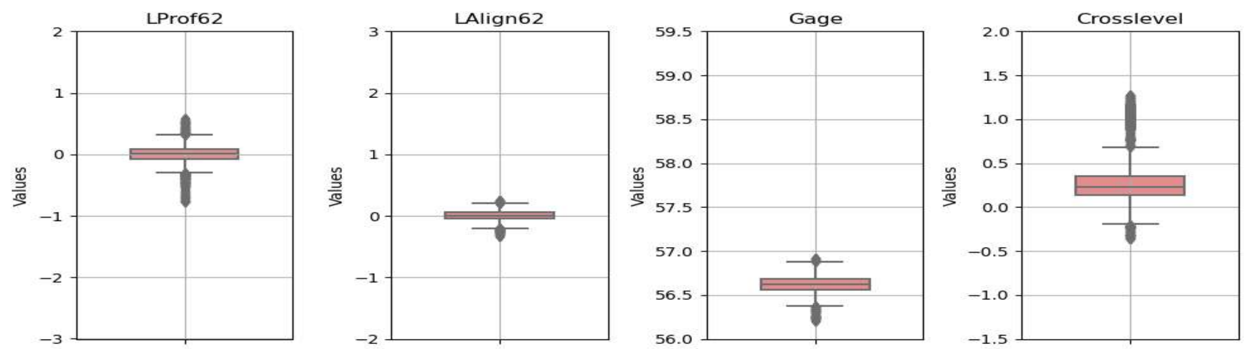

Figure 10: Box and whiskers plot (MP: 58)

3.4. Histograms

These histograms generated from the geometry data show a symmetric distribution centered around zero. The shape is roughly Gaussian (bell-shaped), indicating a normal distribution with most of the data points clustering near the mean value. However ‘crosslevel’ exhibited a bi-modal distribution in both track sections (mileposts 56 and 58) suggesting two predominant states in crosslevel measurements. This might indicate regular alternations or shifts in track leveling, which could be an intentional feature or reflect periodic deviations. The visual analysis of the histograms indicates that although the geometry parameters exhibit a similar normal distribution pattern, the extended tail for the track section around milepost 56 (Figure 11) suggests greater irregularities in this segment compared to the track section around milepost 58 (Figure 12), which shows a tighter clustering of values around the mean.

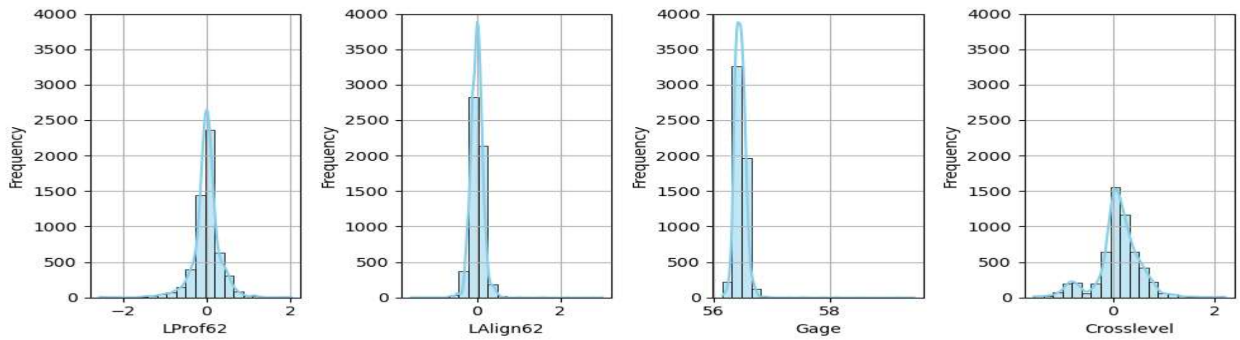

Figure 11: Histogram (MP: 56)

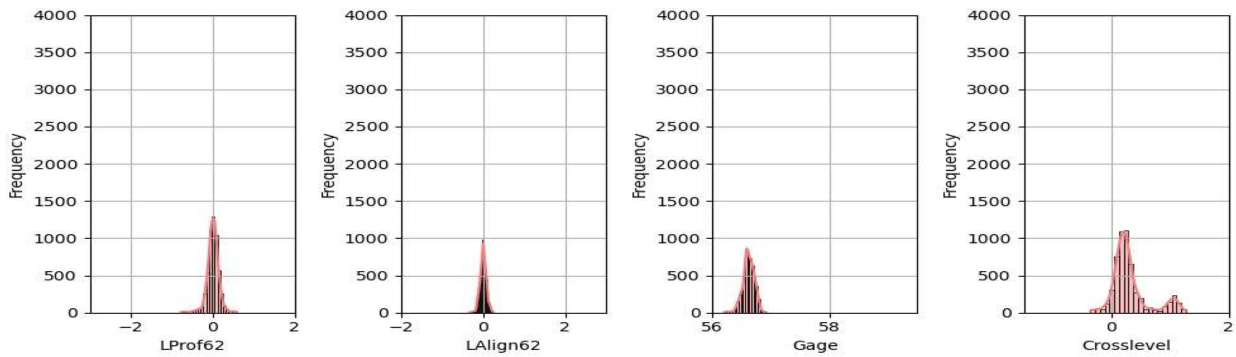

Figure 12: Histogram (MP: 58)

3.5. Correlation Matrix

As shown in the correlation matrix (Figure 13) the correlation values of 0.78 and 0.74 indicate a strong positive relationship between the left and right profiles and alignments of the track respectively. This suggests that deviations in track profile and alignment tend to occur symmetrically, meaning that if one side of the track deviates from the norm, the other side is likely to show a similar deviation. There is a slight positive correlation (0.24) between gage and alignment which suggests mild interdependencies that could be explored further in detailed analyses. Most of the other parameters show very low correlation with each other (close to 0). This indicates that each parameter mostly varies independently, which could imply that different factors or conditions affect each aspect of the track geometry.

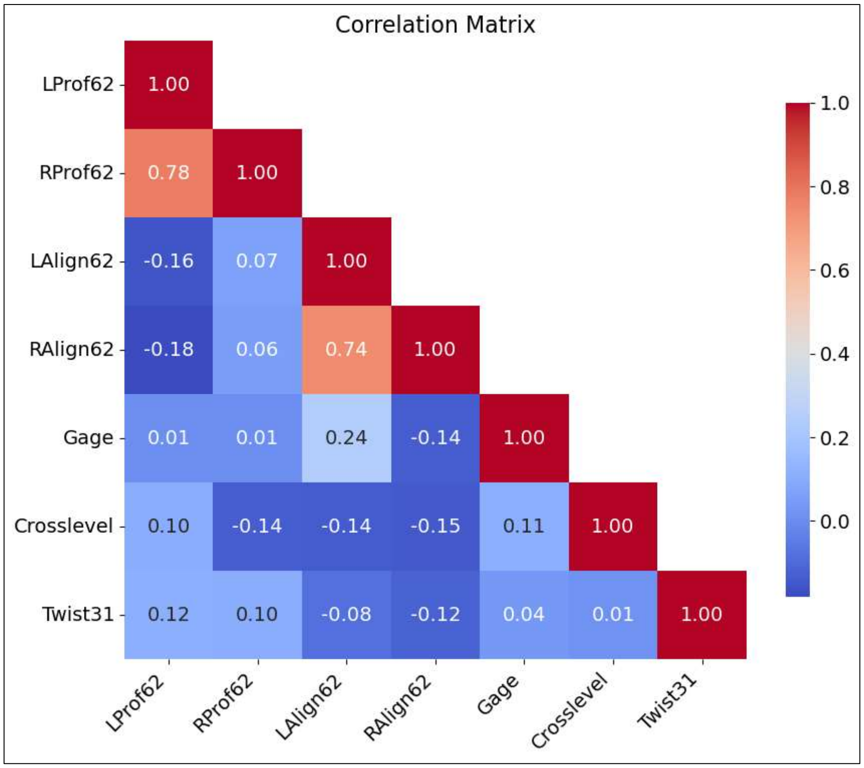

Figure 13: Correlation Matrix

4. Results and Discussion

In this research, the left profile signal (LPof62') for the 5 miles (8 km) track was preprocessed and analyzed. In the case of fixed-length segmentation, the 5 miles signal was divided into a predefined length of 1/20th of a mile (264 feet) or 80.5 meters. This generates 100 segments with varying signal characteristics. In the case of dynamic (variable length) segmentation, "l2" model based change point detection algorithm was utilized to generate about 48 segments from the 5 miles track. Figure 14 and Figure 15 show the fixed and variable length segments for a sample 1 mile section of the data.

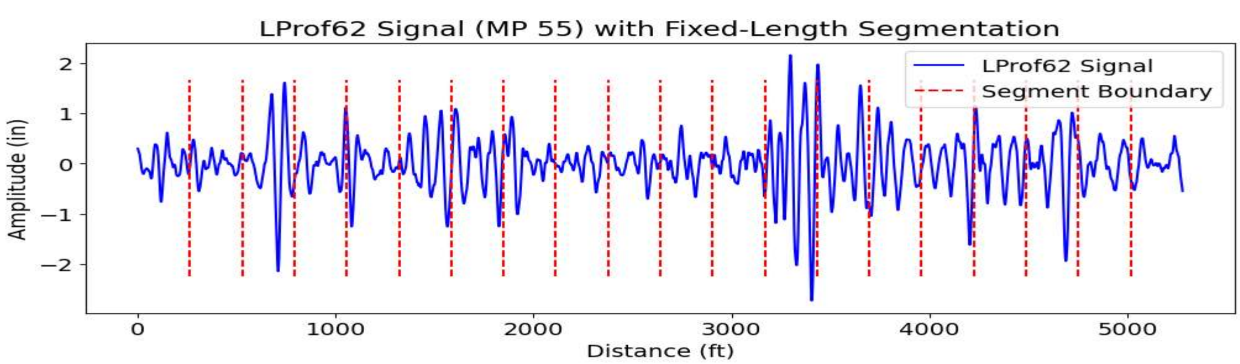

Figure 14: Fixed-length segmentation

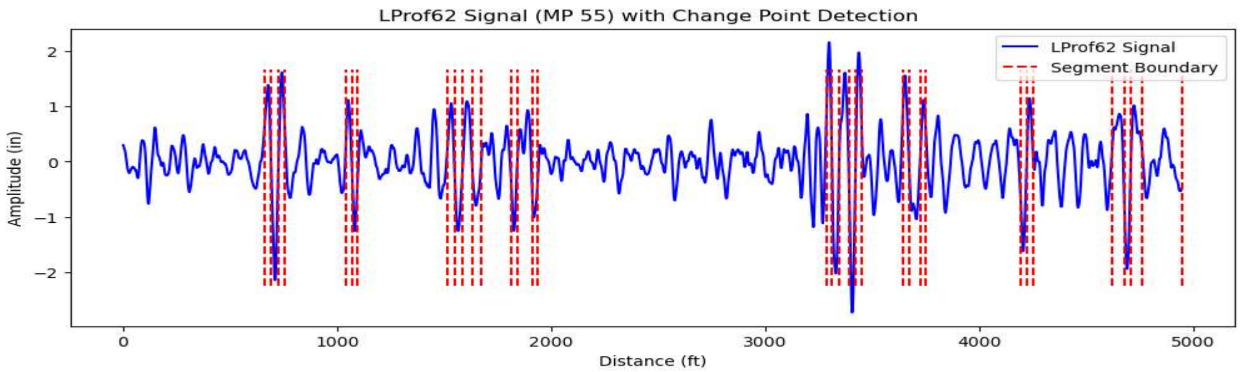

Figure 15: Dynamic (variable-length) Segmentation

The performance of each segmentation methods was evaluated based on (1) computational efficiency of the method, (2) signal/data stability across segments and (3) discriminability of each method. Computational efficiency was measured based on metrics such as run-time and memory usage of each segmentation methods. The stability or consistency of the signals across the segments during the segmentation process was measured using the signal-to-noise ratio of each segments. The discriminative power of features extracted from each segmentation method was measured using statistical tests such as Fisher-score and f-test.

4.1. Computational Efficiency

Table 1 shows the summary of results for the for the performance metrics that evaluates computational efficiency and signal stability of the fixed-length and dynamic segmentation techniques.

Table 1: Computational Efficiency and Signal Stability

	Fixed-length	Dynamic (variable-length)
Run Time (sec)	0.2	306
Memory Usage (MB)	1.66	1.65
SNR (std. dev)	0.09	2.2

The change point detection algorithm (l2 model), used for dynamic segmentation, exhibits poor computational efficiency, with a total run-time of **306 seconds** to process five miles track compared to just **0.2 seconds** for the fixed-length approach. The dynamic segmentation's complexity, which could include extra calculations, iterative procedures, or adaptive mechanisms that lengthen processing times, could be the cause of the significant discrepancy. Both methods used almost the same amount of memory, being 1.66 MB for the fixed system and 1.65 MB for the dynamic segmentation processes. Despite the large difference in run time, the small difference in memory usage indicates that both methods are efficiently tuned, with no visible memory consumption tradeoff. This finding suggests that higher memory needs are not the cause of the dynamic system's longer run time. The significant difference in run time underscores the high computational complexity of the change point detection method, which requires more processing time to adaptively identify segments based on signal changes. This makes it less practical for large datasets or real-time applications.

4.2. Signal Stability

The standard deviation of the Signal-to-Noise Ratio (SNR), shows a significant difference between the two methods. With a significantly lower signal-to-noise ratio (SNR) deviation of 0.09, the fixed system exhibits higher signal reliability and consistency across segments. On the other hand, the dynamic segmentation method exhibits greater inconsistency in signal performance, as evidenced by its higher deviation of 2.2 shown in (Table 1). This instability in signal power across segments using the "$l2$" model based change point detection algorithm suggests that the dynamically divided segments may not consistently capture meaningful signal patterns, leading to increased noise and variability. In contrast, the fixed-length method shows much more stable signal power, with a lower SNR variation across segments.

4.3. Discriminative Power (statistical Test)

All the segments in the five track mile data were classified into two categories (ride quality and safety) based on the FRA's safety standard for class 6 track. The safety threshold stated in this standard stipulates the amplitude exceedance of 0.75 inches for a profile (vertical alignment). Segment with the amplitude of the profile signal exceeding 0.75" were labelled as a 'safety' and those with amplitude values under 0.75" were labelled as a 'ride quality' class. Metrics such as Fisher Score and F-test were used to evaluate how well the extracted features from each segmentation method differentiate between ride quality and safety segments.

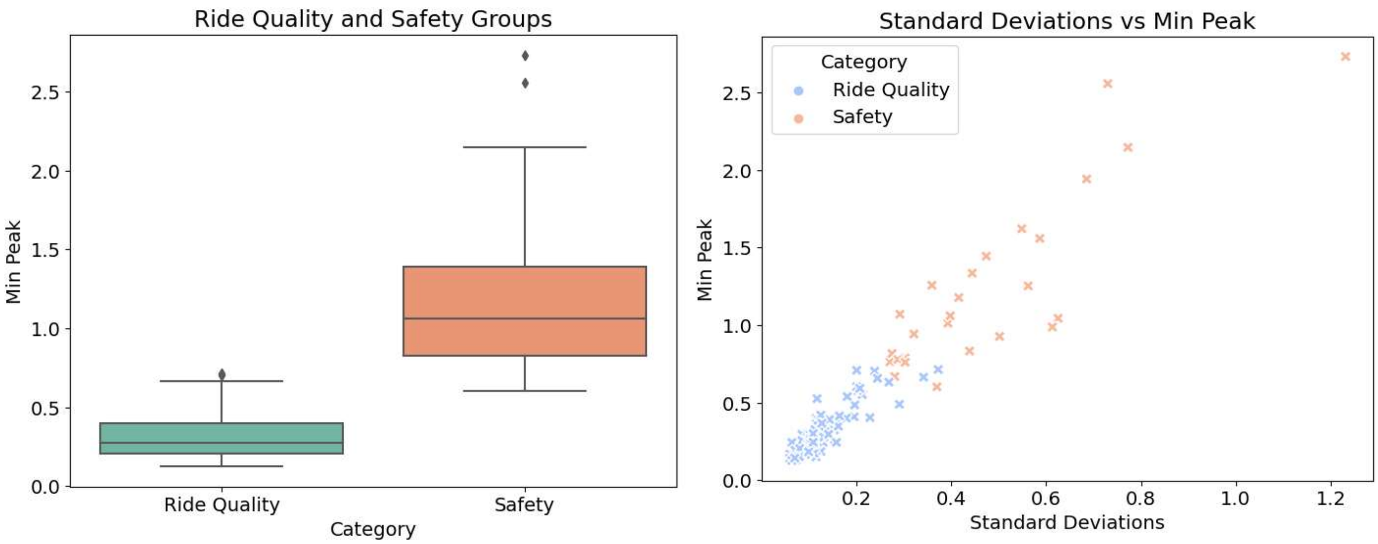

Figure 16: Ride Quality and Safety classes of the track segments

The minimum and maximum values, standard deviation, energy, kurtosis and skewness are extracted from both fixed-length and dynamic segments. The f-value, derived from ANOVA (Analysis of Variance), quantifies the degree to which these features vary between safety and ride quality groups compared to the variation within each group. It provides a ratio of between-group variance to within-group variance, where higher values indicate better discriminability. Similarly, Fisher-score measures the separation between classes (safety and ride quality) by calculating the ratio of the variance between the classes to the variance within the classes for each feature. Table 2 shows the summary of these statistical tests for both segmentation techniques.

Table 2: Feature Discriminability

	Fixed-Length			**Dynamic (Variable-Length)**		
	Fisher-score	**f-value**	**p-value**	**Fisher-score**	**f-value**	**p-value**
Min	1.68	168.36	3.66E-23	0.01	0.4875	0.4886
Max	1.66	165.70	6.04E-23	0.005	0.0241	0.8772
Std. dev	1.66	165.62	6.13E-23	0.06	2.76	0.10
Energy	0.59	58.53	1.27E-11	0.02	0.83	0.37
Kurtosis	0.11	10.70	0.001471	0.003	0.13	0.72
Skewness	0.04	3.72	0.06	0.004	0.18	0.68

This result shows across all features, the fixed-length method constantly exhibits a larger Fisher score and F-value, highlighting its greater discriminatory potential. Features from the dynamic segmentation method on the other hand, resulted in far lower Fisher-score and F-values. These low values imply that the dynamic system's feature contribution is not sufficiently variable, which reduces its capacity to discriminate between important characteristics of the data. Considering the confidence interval of 95%, in the case of the fixed-length segmentation method, the $p-values$ associated to the f-test came under 0.05 indicating a strong statistical significance. However, in the case of dynamic segmentation method the $p-values$ for all the features are above 0.05, indicating a lack of statistical significance in distinguishing between safety and ride quality classes. All of these results point to the fixed –length segmentation method as the more effective and statistically dependable option for applications that need feature extraction and discrimination between different characteristics of the data.

5. Conclusion and Future Direction

The use of change point detection, particularly the "l2" model, for dynamic segmentation in non-stationary spatial signals, such as railway track geometry data, has shown poor performance. While the method theoretically offers flexibility by adapting to natural signal variations, its high computational cost and inconsistency in signal segmentation severely limit its practical utility. The dynamic approach not only requires significantly more processing time but also struggles to maintain consistent signal power across segments and fails to effectively distinguish between safety and ride quality features. In contrast, fixed-length segmentation has proven to be a more efficient and reliable method, providing superior data stability, faster computation, and significantly better discriminative power. Therefore, despite its theoretical advantages, dynamic segmentation using change point detection (l2 model) is not recommended for this type of non-stationary spatial data at least for feature extraction and discriminations tasks.However, fixed-length segmentation emerges as the more practical and effective solution. Future research should focus on exploring alternative adaptive models, such as Bayesian or machine learning-based approaches, to improve the accuracy and efficiency of dynamic segmentation for non-stationary spatial data.

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