Enhancing Road Infrastructure Quality Assessment Through Low-Cost Inertial Sensors

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Abstract:

The quality of road infrastructure significantly influences road safety, vehicle performance, and the overall driving experience. Traditional methods of assessing road quality, such as manual inspections, often lack the efficiency and accuracy needed to address modern transportation challenges. To overcome these limitations, this project focuses on developing an innovative model to assess road roughness using sensor data. The model leverages Android sensor technologies, primarily utilizing two types of sensors: accelerometers (inertial sensors) and GNSS (Global Navigation Satellite System) sensors. Given resource constraints, data was collected using an Android phone mounted on bicycles, which provided valuable insights despite some challenges and errors encountered during data collection. At the core of our model is the analysis of the International Roughness Index (IRI), which has been widely recognized as a reliable indicator for assessing road roughness on a quantitative scale. By deriving the parameters associated with IRI and applying the proposed formulae, we were able to recognize and categorize road surface irregularities such as potholes and humps. Our approach was further validated through the application of statistical methods, including the Kolmogorov-Smirnov (KS) test and Q-Q (Quantile-Quantile) plots. These methods demonstrated that the IRI is indeed a robust metric for indicating road roughness and low-cost sensors can be used for estimating road roughness. The metrics established in this study can serve as the foundation for developing more sophisticated algorithms that assess road roughness based on accelerometer data, ultimately contributing to enhanced transportation efficiency and road safety.

1. Introduction

The backbone of modern economies, transportation infrastructure, is undergoing unprecedented strain due to increasing urbanization and vehicular traffic. India, a rapidly developing nation, faces significant challenges in maintaining and improving its road network. The consequences of suboptimal road conditions are far-reaching, encompassing economic losses, environmental degradation, and, most critically, a heightened risk of road accidents.

India possesses one of the largest road networks in the world, spanning millions of kilometres and serving as a critical component of the nation's transportation system. Roadways are the predominant mode of transport, particularly for short distances, due to their cost-effectiveness and convenience. They facilitate door-to-door service, minimize loading and unloading costs, and connect remote areas to major transport hubs, including railway stations, airports, and seaports. Despite the importance of road transport, India faces a significant road safety crisis. India witnessed a troubling surge in road accidents during 2022. According to the Ministry of Road Transport and Highways, the number of road accidents reached 461,312, resulting in a staggering 168,491 fatalities and 443,366 injuries (The ministry of road transport and highways India 2022).These figures represent a significant increase compared to the previous year. Analysing the data, it's evident that a concerning 36.53% of road accidents in India resulted in fatalities, while a substantial 96.09% led to injuries.

The alarming rise in road accidents underscores the urgent need for enhanced road safety measures and improved infrastructure. Addressing pavement roughness and fostering road safety awareness are essential for reducing fatalities and promoting safer transportation across the country.

The motivation for this project on road roughness analysis using inertial sensors stems from the pressing challenges within India's road transportation system. The increasing accident rate, often linked to deteriorating pavement conditions, necessitates a more effective monitoring and maintenance strategy. By leveraging low-cost inertial sensors, this papers aims to provide a robust solution for detecting and quantifying pavement roughness. This approach will enable the prediction of road degradation, enhance ride quality, and reduce vehicle delays, fuel consumption, and maintenance costs. Ultimately, the goal is to improve road safety and efficiency, contributing to a more reliable transportation network in India.

1.1 Traditional Road Assessment Limitations

Traditional road roughness assessment methods in India face significant challenges that limit their effectiveness and scalability. One of the primary concerns is the high cost and equipment requirements of techniques like profilometers, roughometers and laser-based systems. These methods, while precise, are expensive to deploy on a large scale, particularly in remote or rural areas where financial and logistical constraints are more prominent (Chenglong Liu , Difei Wu, Yishun Li , Yuchuan Du 2021). Furthermore, these methods are time-consuming and labour-intensive, as they often rely on manual inspections or specialized vehicles, which slows down the process of identifying and rectifying road issues.

Another limitation is that traditional methods are typically focused on major highways and roads, leaving many secondary and rural roads unmonitored. This lack of coverage poses safety risks, as road deterioration in these areas may go unnoticed for long periods. Additionally, manual inspections are prone to human error and subjectivity, leading to inconsistencies in data collection. Even mechanical or laser-based methods can yield variable results due to differences in calibration, equipment condition, or operator technique .

The inaccessibility of remote, hilly, or conflict-prone regions presents another challenge, as traditional methods struggle to reach these areas. Furthermore, many of these techniques require road closures or traffic diversions during measurements, which disrupts traffic flow and inconveniences road users. Environmental factors like rain, snow, or fog can also impact the accuracy of measurements, further complicating the process.

Lastly, traditional methods often produce data that is difficult to integrate with modern digital systems for road management and predictive maintenance. This makes it harder to develop real-time, data-driven strategies for road upkeep, leaving much room for improvement in how road conditions are monitored and maintained.

1.2 The Advent of Mobile Sensing

Recent advancements in mobile technology present a promising solution to address the challenges associated with traditional road roughness measurement. Smartphones, which are now ubiquitous, come equipped with various sensors such as accelerometers and GNSS that can capture essential data for evaluating road conditions. By utilizing these sensors, it becomes possible to develop a scalable and cost-effective method for assessing road quality.
By harnessing smartphone sensors (e.g., accelerometers and GPS), this paper offers a cost-effective, scalable, and efficient alternative to traditional methods of measuring road roughness. With data collected from widely available devices, the proposed model can cover vast areas at lower costs, provide frequent updates, and be implemented even in remote regions. Additionally, the matrix system designed within the project can facilitate real-time data analysis and support more effective road maintenance planning, ultimately enhancing road safety and transportation across India..

2. Research Objectives

This paper which focuses on measuring road roughness and creating a matrix system for analysis, can greatly improve road transportation in India by identifying and addressing hazardous road conditions. By pinpointing areas with significant roughness, the model can help prioritize road repairs, enhancing overall road safety and reducing the risk of accidents caused by poor road surfaces. Additionally, this system can assist in planning preventive maintenance, leading to more efficient road management and safer driving experiences for millions of road users across the country**.**

This study aims to investigate the feasibility of using mobile phone sensors to estimate road roughness. By analysing accelerometer and GNSS data collected during vehicular movement, the paper aims to develop a robust algorithm for quantifying road irregularities. The research will contribute to the development of a comprehensive framework for road assessment, facilitating data-driven decisions for infrastructure improvement and enhanced road safety. The objectives of this paper are:

1. Exploring the correlation between accelerometer observations and road roughness.
2. Developing algorithms to extract relevant features from sensor data.
3. Creating a road roughness index based on extracted features.

By addressing these objectives, this research seeks to contribute to the advancement of road infrastructure assessment and ultimately contribute to improving road safety in India.

3. Literature Review

Research on road surface roughness measurement has evolved with the integration of affordable technologies like smartphones and GPS systems. Zang et al. (2018) introduced a method using GPS and accelerometer sensors on bicycle-mounted smartphones to assess road roughness. Their approach, which calculates the International Roughness Index (IRI) and detects road features like potholes, showed a high correlation with professional instruments, making it a viable option for crowdsourcing road data in non-motorable areas.

Bidgoli et al. (2019) expanded on this by developing a cost-effective system for motorable roads. Using an extra wheel with accelerometers and GPS, their system accurately calculated the IRI, achieving an 87% coefficient of determination with low error margins. This further demonstrates the feasibility of using simple sensors for large-scale road monitoring. Rao et al. (2023) took a safety-focused approach, evaluating road conditions through a multi-criteria technique and Artificial Neural Networks (ANN). They highlighted how poor road conditions impact safety and suggested mitigation strategies, emphasizing the need for comprehensive studies on road infrastructure.

Additionally, Kumar et al. (2018) evaluated the structural integrity of low-volume roads using non-destructive techniques. Their study compared the Light Weight Deflectometer (LWD) and Benkelman Beam Deflectometer (BBD), revealing useful insights into road overlay thickness and its variations, which inform future pavement management practices. Together, these studies provide insights into low-cost, scalable methods for road roughness assessment, offering significant potential for improving road safety and infrastructure management.

4. Methodology

The smartphone equipped with GNSS, and inertial sensors is installed a bicycle. A fundamental aspect of the experiment was the smartphone's installation position. It was recognized that mounting the device on different parts of the bicycle would lead to variations in acceleration data. To capture consistent road roughness measurements, the was securely mounted on the top tube of the bicycle's main frame. This location was chosen to minimize instability-related errors, ensuring the phone remained steady during rides, which in turn enhanced the reliability of the recorded data.

The decision to utilize a bicycle as the vehicle for this experiment was intentional. Bicycles, with their rigid structure, are highly sensitive to road irregularities, making them ideal for capturing detailed road surface data. To further mitigate interference from suspension systems—which could dampen vibrations from uneven surfaces—the bicycle employed in this study was specifically designed without suspension. This design allowed the mounted sensors to directly record the impact of road conditions on the bicycle's movement.

Prior to data collection, the smartphone's sensors were calibrated to align the z-axis of the accelerometer with the direction of gravitational acceleration. This calibration was crucial for ensuring vertical measurements accurately reflected the true vertical displacements experienced during the ride. Additionally, the cyclist maintained a stable speed to reduce variations in data caused by changes in velocity or instability, thereby enhancing the overall accuracy of the measurements.

The experiment operated under several assumptions regarding road conditions and data capture methods. One key assumption was that roads were relatively flat. For roads with sufficiently large slopes, a correction needs to be applied. Consequently, vertical acceleration was selected as the primary metric for analysing road roughness, allowing the model to account for road gradients. Moreover, the experiment assumed relatively straight-line motion to simplify velocity calculations, approximating velocity as equal to speed for streamlined data analysis.

Figure 1 : Setup of the smartphone on crossbar of the bicycle.

The choice to mount the smartphone on the top tube, rather than on the handlebars, was another significant consideration. Handlebar-mounted sensors are prone to noise from the frequent movements and turns during cycling, potentially introducing errors into the data. By selecting a more stable mounting point on the bicycle frame, the experiment aimed to minimize such disturbances, ensuring more accurate and consistent data collection.

Given the extensive dataset available for analysis, the study focused on evaluating 3-meter sections of roads rather than assessing entire road lengths. This targeted approach facilitated a detailed examination of specific road conditions, such as potholes and irregularities. Analysing smaller segments allowed for a more precise identification and characterization of localized issues, leading to improved assessments of road surface roughness and better insights into maintenance needs.

This paper leveraged the unique sensitivity of bicycles to road irregularities, combined with careful sensor placement and calibration, to capture precise data on road roughness. The results are intended to inform more effective road maintenance strategies, ultimately contributing to improved ride quality and road safety. This paper addresses existing research gaps by proposing a method for measuring road surface roughness in bicycle and pedestrian lanes using GNSS and accelerometer sensors on bicycle-mounted smartphones, with a focus on IRI. We analyse the computing model of road surface roughness, deriving IRI model parameters from smartphone sensors, and introduce an algorithm to identify potholes and humps.
To validate IRI's efficacy as a true measure of road roughness, we conduct statistical analyses, including Quantile-Quantile (Q-Q) plots and the Kolmogorov-Smirnov (KS) test, to assess sensor data reliability. Inertial sensors (accelerometers) record vertical accelerations due to road irregularities, while GNSS provides precise geolocation data. The integration of these datasets enables comprehensive road condition analysis. The statistical analysis examines data distribution using Q-Q plots and the KS test to compare empirical sensor data against theoretical distributions, further validating measurement consistency.

4.1 International Roughness Index

Road surface roughness is a complex characteristic without a universal definition, typically assessed through three stages: data collection, preparation, and quantitative analysis. This study employs the International Roughness Index (IRI) (Smith, K. and Ram, P 2016, Sayers, M.W. 1995) as the primary metric for quantifying road surface unevenness.
The IRI is a standardized measure derived from longitudinal road profile measurements, quantifying the impact of pavement irregularities on vehicle suspension. Calculated using a quarter-car vehicle mathematical model (Smith, K. and Ram, P 2016), IRI represents a cumulative response expressed in slope units. While generally computed per wheel path, it can also yield a Mean Roughness Index (MRI) when data from both wheel paths are available. Compared to other pavement performance indicators like the Pavement Condition Index (PCI) (St. Maryam H, Bulgis and Rustam Madami 2023), IRI exhibits lower stochasticity and subjectivity, though variability can arise from differences in test vehicle runs and discrepancies between wheel path readings (Piryonesi, S. M. (2019), Piryonesi, S. Madeh; El-Diraby, Tamer E. (2020-09-11). Since its introduction in the mid-1980s, IRI has become the global standard for road evaluation, mandated for reporting to the United States Federal Highway Administration and defined by ASTM International standards (e.g., ASTM E1926, ASTM E1364). Additionally, IRI plays a critical role in new pavement assessments and contractual agreements based on smoothness.

4.1.1 Measurement model:

For example, for a vehicle driving on a road like that shown in the figure below, t_i ($i \in [1,n]$) is the sampling time, and h_i is the longitudinal offset of the road surface at ti. Through calculation, the vertical displacement (Vh_i) of each sampling interval can be obtained:

$$Vh_i = |h_i - h_{i-1}| \quad (1)$$

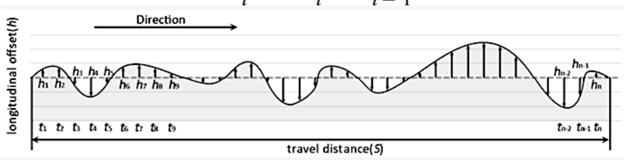

Figure 2: Example of a road longitudinal profile.

According to the IRI definition (Sayers, M.W. 1995), the index can be computed by accumulating the total vertical displacement across all sampling intervals, then dividing this sum by the total travel distance S**.**

$$\text{IRI} = \frac{\sum_{i=2}^{n} Vh_i}{S} = \frac{\sum_{i-2}^{n} |h_i - h_{i-1}|}{S} \quad (2)$$

Using the IRI on a road with a slope can be challenging but not impossible. The IRI is designed to measure the smoothness of a road surface and is typically computed using vertical height variations of the road. On the other hand, we presume that the road is relatively flat. When dealing with sloped roads, the main issue is that the vertical height measurements might be influenced by the road's incline, which could lead to inaccurate assessments of roughness.

Therefore, when computing IRS, we must know the total travel distance and the vertical displacement value of each sampling time. Travel distance can be computed via the GPS location. However, vertical displacement is not a value that can be obtained directly and can be derived from the output of the accelerometer sensors. α_{ν} is vertical acceleration. It is the second derivative of Vh. Vh is the vertical displacement. Therefore

$$\sum Vh = \iint_{t_{start}}^{t_{stop}} \left|\alpha_{\nu}\right| (dt)^{2} \tag{3}$$

Given the inaccuracy of the data, smaller time intervals are used to minimize the amplification of errors.

$$\text{IRI} = \frac{\sum_{i=2}^{n} Vh_i}{S} = \frac{\iint_{t_{start}}^{t_{stop}} \left|\alpha_{\nu}\right| (dt)^{2}}{S} \tag{4}$$

Vertical Acceleration calculation : In order to address the problem of sloped roads, vertical acceleration can be used to compute road roughness instead of directly using the height difference. The process involves the following steps:

- Reference Vector: The first data point in the acceleration data is used as the reference vector, assumed to be (0, 0, g), where g represents the acceleration due to gravity (approximately 9.8 m/s²), and the device is considered to be at rest and oriented horizontally.

- Scalar Projection: For each data point, vertical acceleration is derived by projecting the acceleration vector onto the reference vector. This is achieved by calculating the dot product between the current acceleration vector and the reference vector, and then normalizing this value by dividing it by the magnitude of the reference vector.

This approach allows for an accurate measurement of vertical acceleration that is less influenced by the road's slope.

4.1.2 Vertical Acceleration calculation: To determine vertical acceleration, we establish an initial reference point. Assuming the device is stationary and horizontally oriented at the data's beginning, a reference vector of (0, 0, g) is defined, where g is the acceleration due to gravity. For each subsequent data point, vertical acceleration is calculated by projecting the acceleration vector onto the reference vector. This involves computing the dot product of the current acceleration vector and the reference vector, followed by dividing the result by the magnitude of the reference vector. As the smartphone's installation and orientation on the bicycle are unknown and variable, vertical acceleration may appear in any dimension of the tri-axial accelerometer data. Therefore, the z-axis acceleration cannot be directly taken as vertical acceleration, requiring a method to derive it from tri-axial values

In the acquisition process, we set a requirement in advance: when the bicycle rider started the recording, the bicycle had to be in the normal riding posture, and kept stationary for more than 5 s. As the smartphone, which is mounted on the bicycle, is stationary, the only force it receives is the gravitational one, and the direction is vertical and downward, with a value of 1 g. Therefore,

$$\overline{A_x} * \overline{A_x} + \overline{A_y} * \overline{A_y} + \overline{A_z} * \overline{A_z} = 1 \tag{5}$$

where $\overline{A_x}$, $\overline{A_y}$, and $\overline{A_z}$ are the average acceleration values of the *x*, *y*, and *z* axes in these 5 s, obtained from the accelerometer sensor on the smartphone .Deriving the vertical acceleration (α_{ν}) from any tri-axial acceleration output $A = \left(A_x, A_y, A_z\right)$ can be considered as projecting the vector A onto the reference vector $\overline{A} = \left(\overline{A_x}, \overline{A_y}, \overline{A_z}\right)$, measured at the beginning of the acquisition process. In other words, α_{ν} is the scalar projection of vector A and $\overline{A}$.

$$\alpha_{\nu} = \frac{A \cdot \overline{A}}{|\overline{A}|} = \frac{A_x * \overline{A_x} + A_y * \overline{A_y} + A_z * \overline{A_z}}{\sqrt{\overline{A_x} * \overline{A_x} + \overline{A_y} * \overline{A_y} + \overline{A_z} * \overline{A_z}}} = A_x * \overline{A_x} + A_y * \overline{A_y} + A_z * \overline{A_z}$$

(6)

4.1.3 Calculating the travel distance: There are two methods for calculating travel distance (S). The first method uses GNSS to obtain the longitude and latitude coordinates of each sampling point. The travel distance is then computed by summing the distances between each pair of adjacent points. The distance between two sampling points can be approximated using the **Haversine formula [E Maria *et al* 2020]**, which is specifically designed for this purpose.

$$d = 2 * R * \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1) * \cos(\varphi_2) * \sin\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \tag{7}$$

where $\varphi 1$ and $\lambda 1$ are the latitude and longitude of point 1, $\varphi 2$ and $\lambda 2$ are the latitude and longitude of point 2, and R is the Earth's radius (mean radius = 6371 km).
Alternatively, the travel distance can be computed using the travel speed measured at each sampling point. Specifically,

$$S = \int_0^t V_t dt \tag{8}$$

While inertial sensors theoretically offer the capability to calculate distance by integrating speed measurements, practical limitations arise when using a simple setup like a phone mounted on a bicycle handlebar. The inherent susceptibility of inertial sensors to noise, drift, and vibrations induced by the dynamic cycling environment can significantly compromise the accuracy of integrated distance calculations (Kok, Manon & Hol, Jeroen & Schön, Thomas 2017). Additionally, challenges in maintaining precise sensor calibration and accounting for complex motion patterns during cycling further hinder the reliability of this approach. In contrast, GNSS-based location data offers a more direct and robust method for determining distance travelled . By providing precise geographic coordinates, GNSS can accurately calculate distance based on changes in position, mitigating the impact of sensor errors and effectively handling the complexities of cycling routes. Consequently, relying on GNSS location data is generally preferred for distance estimation in road roughness assessment.

Smartphone GNSS typically provide location accuracy within 10 meters, while instantaneous speed accuracy ranges from 0.1 to 0.2 m/s according to manufacturers (Jeonghyeon Yun , Cheolsoon Lim and Byungwoon Park 2022). However, due to the inherent challenges of maintaining a perfectly straight path while cycling, using instantaneous speed to calculate total travel distance is impractical. To address this, data segmentation is

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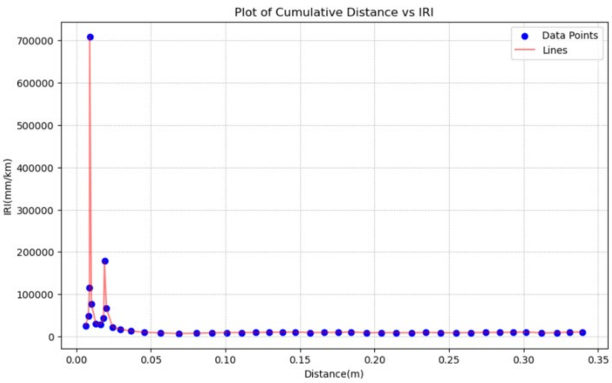
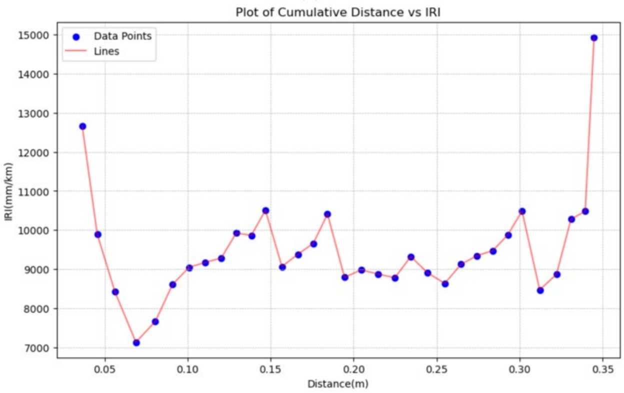
employed. Assuming an average speed covers 10 meters in approximately 3 seconds, both accelerometer and location data are divided into 3-second segments to calculate IRI for each 10-meter patch. Accordingly we have segmented both the location and inertial data.

5. Results and discussion

IRI can be used as a measure of road quality and it varies significantly over short distances due to localized road irregularities. Therefore as mentioned in 4.1.3 the data was segmented into 10-m patches, and an IRI value was computed for each patch of both rough and smooth roads. The resulting graphs from this analysis are presented below, demonstrating the variations in IRI values across different road conditions.



(a)

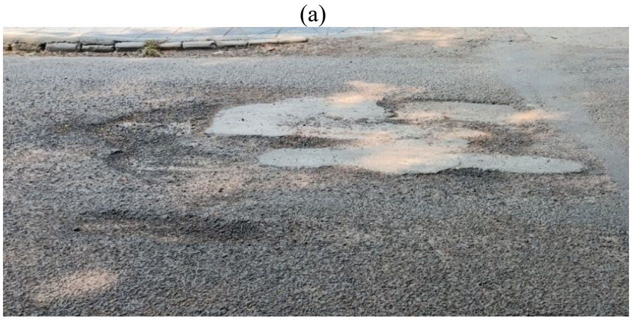


(b)

Figure 3 : The IRI obtained for the smooth (a) and rough (b) roads as shown in the graphs above.

The plots demonstrate that the smooth road exhibits minimal deviation in IRI values over time, stabilizing after an initial period. In contrast, the IRI for the rough road continues to fluctuate significantly as potholes and other surface irregularities are encountered. This consistent variation highlights the impact of road anomalies on IRI measurements for rough surfaces.

(a)



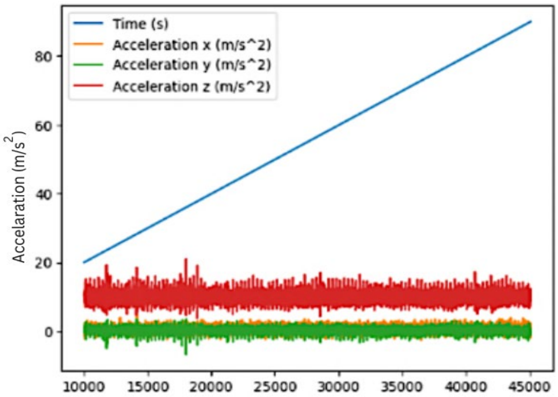
(b)

Figure 4 : Road anomalies such as potholes (a) and (b)

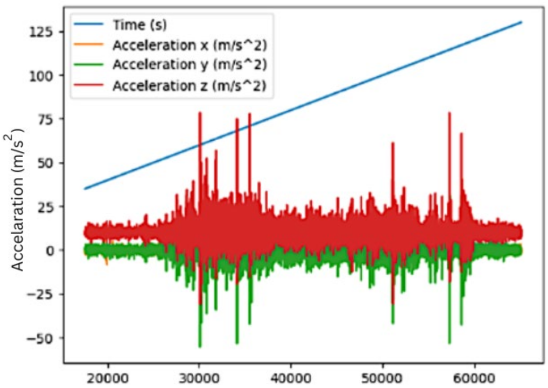
Up to this point, an established index (IRI) has been utilized to quantify road roughness. To further validate the accuracy of this measure, the focus will now shift to applying statistical models to the collected data. It is important to note that all analyses were conducted on the same set of roads, ensuring consistency in the evaluation process.

5.1 Distribution Analysis

Following are the plots for acceleration in tri-axial directions for a rough road and a smooth road-



(a)



(b)

Figure 5 : Acceleration plot for smooth (a) and rough road (b)(The horizontal axis shows the number of data points captured).

As seen in Figure 5, the acceleration varies significantly on rough roads, whereas the disturbance on smooth roads is comparatively insignificant. Total acceleration was calculated using all three accelerations measured in the inertial data, followed by plotting a distribution curve to analyse the data's nature. It helps to

understand the distribution of acceleration on a smooth road. Essentially, we aim to establish a reference point using the smooth road which will be used to compare and analyse comparatively rough road conditions.
The data obtained from the smooth road was initially analysed, resulting in a histogram that displayed the data distribution as shown below:

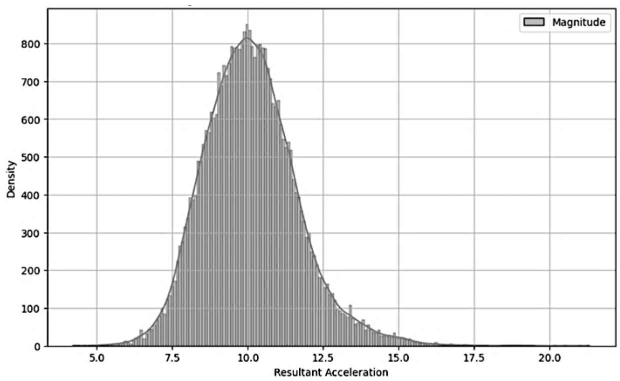


Figure 6: Histogram and KDE of the resultant acceleration of smooth road data.

Based on the graph we proposed a Hypothesis**:** The dataset for a smooth road follows the normal distribution closely and deviates as the road gets more and more rough. This indicates that while traveling on a smooth road, the collected data closely adheres to a normal distribution pattern. This hypothesis suggests that the acceleration data collected from a smooth road will exhibit a pattern that closely resembles a normal distribution. A normal distribution is characterized by a bell-shaped curve, where the majority of data points cluster around the mean (average) value, with fewer data points occurring at the extremes.
The assumption is that as the road surface becomes rougher, the acceleration data will increasingly deviate from this normal distribution pattern. This deviation might manifest in various ways, such as:

- **Increased spread:** The data points become more dispersed, leading to a wider distribution.
- **Skewness:** The distribution becomes asymmetrical, with a longer tail on one side.
- **Kurtosis:** The distribution's peak becomes more pronounced or flatter than a normal distribution.

By comparing the distribution of acceleration data from different road conditions to the normal distribution, researchers can assess the degree of roughness of the road surface.
Essentially, the hypothesis posits that the normal distribution serves as a benchmark for smooth road conditions, and deviations from this benchmark can be used to quantify road roughness. Based on the analysis of inertial data captured from smooth roads, particularly focusing on resultant acceleration, we observed that the data closely follows a normal distribution. Using this distribution as a reference point, further analysis of rougher road conditions reveals significant deviations from the normal curve. As road roughness increases, the distribution of vertical acceleration becomes more skewed, indicating higher variability and irregularities in the data. This variation suggests that rougher roads introduce greater inconsistencies in the inertial measurements, and tools designed to identify the underlying distribution can effectively quantify the extent of deviation. Such insights are crucial for assessing road quality and improving the accuracy of roughness metrics like the International Roughness Index (IRI).

In order to assess the distribution of the datasets and create a comparison matrix, we will utilize tools such as the Q-Q Plot and the Kolmogorov-Smirnov (KS) , (Clay Ford 2015, Vance W. Berger, YanYan Zhou 2014) test. These tools will allow us to define the primary distribution patterns of the data and evaluate how closely they align with the reference distribution, helping us quantify any deviations across different road conditions.

5.2 Q-Q plot Evaluation

In a Q-Q plot, the straight line represents the points where the quantiles of the sample data match perfectly with the quantiles of the theoretical distribution (in this case, a normal distribution). This line is often referred to as the 45-degree reference line. If the data points closely follow this line, it indicates that the data adheres to the theoretical distribution.

A Q-Q (Quantile-Quantile) plot is a graphical tool used to compare the distribution of a dataset to a theoretical distribution. It plots the quantiles of the sample data against the quantiles of the chosen theoretical distribution, which is usually the normal distribution. If the data closely follows the theoretical distribution, the points in the Q-Q plot will fall along the 45-degree reference line.

We use the Q-Q plot in this analysis to assess whether the acceleration data from various road surfaces fits a normal distribution. By visually comparing the actual data to the theoretical normal distribution, we can determine how well the data aligns with expected patterns for smooth roads and identify deviations in rougher road conditions. The Q-Q plot is particularly useful in identifying deviations such as skewness, kurtosis, or outliers, which are indicative of road roughness and irregularities.

The Q-Q plot compares theoretical quantiles (X-axis) with the sample quantiles from the acceleration data (Y-axis). A reference line at a 45-degree angle is drawn to represent the perfect fit. For each road type, a separate Q-Q plot is generated, allowing for a visual comparison between the empirical data and the theoretical normal distribution.

Z-Score Approach : To standardize the data, we use Z-scores, calculated by the formula: $Z = \frac{x-\mu}{\sigma}$, where x is the data point, μ is the mean of the dataset and σ is the standard deviation. A Z-score of 0 indicates the data point is at the mean, while Z-scores greater than 2 or less than -2 suggest that the data point is more than two standard deviations from the mean, potentially identifying it as an outlier. For smooth roads, the data points aligned well with the 45-degree line, indicating that the acceleration data follows a normal distribution. This suggests consistent vehicle dynamics, with deviations from the mean typically falling within one or two standard deviations, as expected under normal conditions. In contrast, the data from rougher roads deviated significantly from the 45-degree line, particularly in the tails of the distribution. This implies heavier tails, where extreme values (both high and low accelerations) occur more frequently than expected under a normal distribution. This deviation suggests that rough road surfaces lead to more unpredictable vehicle dynamics, indicative of non-normality. For a clearer understanding, please refer to Figure 6 and 7.

Based on these Q-Q plots, we will apply the Kolmogorov-Smirnov (KS) test to further assess how well the acceleration data from different road types conforms to the normal distribution. The KS test will quantify the degree of deviation between the empirical and theoretical distributions.

5.3 KS-Test

The Kolmogorov-Smirnov (KS) test was used to statistically evaluate whether the vertical acceleration data collected from different road surfaces follows a hypothesized normal distribution. After constructing Q-Q plots, which visually assess the alignment between the empirical data and the theoretical distribution, the KS test offers a quantitative method to confirm or challenge these visual assessments.

The KS test measures the maximum distance between the empirical distribution function (EDF) of the sample data and the cumulative distribution function (CDF) of the theoretical distribution (in this case, the normal distribution). It helps to determine whether the sample data fits the specified distribution.

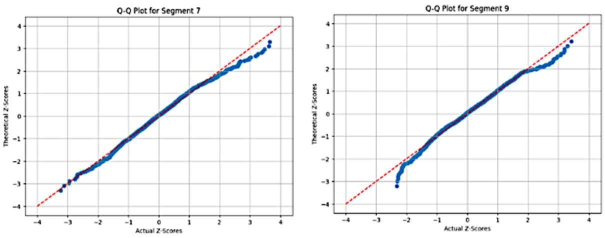
The KS test involves two key variables:
- KS Statistic: This quantifies the maximum difference between the empirical and theoretical distributions. A smaller KS statistic indicates that the empirical data closely follows the theoretical distribution, while a larger value suggests significant deviations.
- P-value: The p-value measures the statistical significance of the observed difference. It represents the probability of observing a KS statistic as extreme as the one calculated, under the null hypothesis that the data follows the assumed distribution. A p-value greater than a conventional threshold (usually 0.05) suggests that we fail to reject the null hypothesis, indicating that the data may indeed follow the hypothesized distribution.

Hypothesis for Road Surface Roughness : The proposed hypothesis states that the acceleration data from smooth roads closely follows a normal distribution, while the data for rougher roads shows increasing deviation from this distribution. To manage the large dataset, the road was segmented into 3-meter sections, allowing for localized analysis of road conditions. In the context of the KS test:
- A p-value > 0.05 indicates that the dataset for that 3-meter segment adheres to the normal distribution, supporting the hypothesis that smooth roads follow a normal pattern.
- A p-value<0.05 suggests that the data significantly deviates from normality, likely due to increased road roughness for that segment.

Integration of the KS Test with Q-Q Plots: While Q-Q plots provide a visual way to assess how well the vertical acceleration data aligns with a normal distribution, they do not give a definitive statistical conclusion. The KS test adds rigor by quantifying the deviation from normality and providing a p-value to statistically verify or refute the observations from the Q-Q plots.

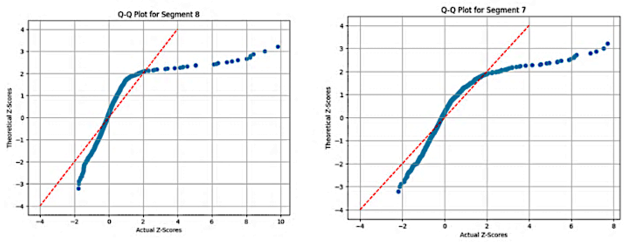
This combined approach of visual and statistical analysis is particularly valuable for road roughness assessment. Smooth road data generally aligns closely with the 45-degree line in the Q-Q plots and returns a high p-value in the KS test, confirming a normal distribution. In contrast, rough road data exhibits greater deviations in the Q-Q plot and returns a lower p-value, indicating that the roughness introduces more extreme values and irregularities, leading to non-normality.

By applying the KS test alongside Q-Q plots, we gain a robust analytical framework that quantifies how different road surfaces—smooth versus rough—affect the distribution of acceleration data. This statistical validation enhances the accuracy of road surface roughness assessments, offering clearer insights into road quality and the effectiveness of metrics like the International Roughness Index (IRI).Following were the plots obtained for different patches of a smooth road. The vertical axis represents the z-score.



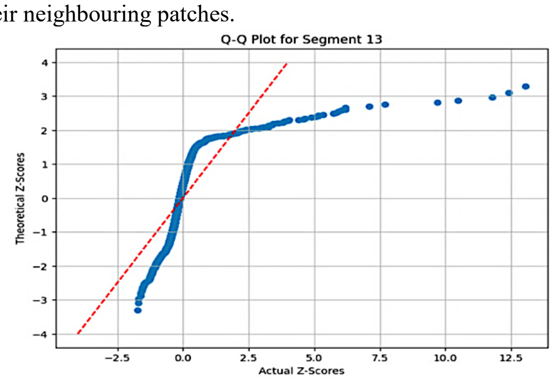
P values:
0.101817241 0.1375432265

Figure 7: Q-Q Plots for different segments of the smooth road. A p value > 0.05 shows that the hypothesis is true and p value < 0.05 shows that the hypothesis is false for a particular road segment. As seen in the figure 4 , a significant number of patches on the smooth road were found to support the hypothesis. However, it is noteworthy that for two patches containing a bump, the resulting plots deviated substantially from the expected pattern, indicating a different behaviour in the data for these sections.



P values:
1.794960 * 10^(-36) 6.873365 * 10^(-30)

Figure 8 : Patches on the smooth road that contained a bump. here in figure 4, the data clearly deviates from a normal distribution, and the p-values are significantly low. For the rough road, the results obtained were opposite. Most of the patches deviated from the normal distribution and p values > 0.05 were rarely found. For speed breakers, the p values of the segments having them were extremely low (in the order of 10^(−132)) as compared to their neighbouring patches.



.
Figure 9 : Q-Q Plot for s segment of the rough road

6. Conclusions and future work

The analysis undertaken in this study focused on evaluating the International Roughness Index (IRI) for various road segments, utilizing statistical models to assess the eligibility of each road type based on its condition. Initially, the IRI was computed for a smooth road, which served as a reference point for the subsequent analysis of rougher road segments. The statistical evaluation began with the identification of the type of distribution for the smooth road data, revealing that it closely approximated a normal distribution. This was further validated through the creation of Q-Q plots, which illustrated minimal deviations from the expected line, indicating a high degree of conformity to normality.

The subsequent application of the Kolmogorov-Smirnov (KS) test provided a rigorous statistical framework to compare the empirical distribution of the acceleration data with the theoretical normal distribution. The results highlighted that the segments of road exhibiting significant deviations in IRI were indeed supported by the interpretations drawn from both the Q-Q plots and the KS test. In contrast, the smooth road's IRI plot remained undisturbed, reinforcing the idea that under optimal conditions, vehicle dynamics are predictable and stable.

Crucially, the hypothesis that the dataset from smooth roads follows a normal distribution and that deviations would occur as road roughness increases was substantiated by the statistical findings. The p-value derived from the KS test was greater than 0.05, leading to the conclusion that there was insufficient evidence to reject the null hypothesis for the smooth road segment. This supports the assertion that the acceleration data from smooth roads can indeed be modelled using a normal distribution. Conversely, the rougher road segments displayed marked deviations, indicating that their IRI values and associated acceleration data diverged significantly from normality.

In conclusion, this analysis introduces a new metric, the p-value, which highlights the distributional characteristics of the accelerometer data obtained from various road surfaces. Across all road types analysed, the accelerometer readings consistently showed that when encountering rough patches—marked by spikes in the data—the corresponding segments deviated significantly from a normal distribution. These deviations were visually evident in the Q-Q plots, which exhibited patterns similar to those presented earlier in the study. Additionally, the results demonstrated that as the length of the road segments analysed decreased, the p-values tended to increase, indicating a closer fit to the normal distribution for smaller patches. This suggests that the roughness of a road can be better captured and quantified over shorter segments, providing deeper insights into the localized variations in road quality. The future work will focus on quantification of road roughness and localization of the potholes on the road.

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