Continuous, response-based road roughness measurements utilising data harvested from telematics device sensors

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Abstract

Roads need to be continuously monitored and maintained to ensure that they offer a driving surface that effectively address the safety and comfort needs of road users. Well maintained roads are also vital for freight transport companies, assisting with minimising vehicle and goods damage that can occur during transportation. Vehicle telematics is technology that is advancing in terms of complexity, diversity and data volume. Hundreds of thousands of these devices are installed in vehicles throughout South Africa and worldwide. The technology is predominantly used for the recovery of hijacked or stolen vehicles, driver behavioural insurance and monitoring and management of vehicle fleets. This paper demonstrates that vehicle telematics provides additional potential in terms of estimating road roughness (similar to a Class 3 level). This is demonstrated by utilising the global positioning system (time, latitude, longitude and speed) and vertical (z) acceleration data harvested from telematics device sensors. Road roughness data obtained from telematics technology can be used as 'screening' devices to measure road roughness on a real-time basis. It can also help close the gap between Class 1, Class 2 and Class 4 road roughness measurements.

Keywords: Class 3 road roughness; telematics technology; global positioning system (GPS); accelerometer; International Roughness Index (IRI); Half-car Roughness Index (HRI); Response Type Road Roughness Measuring System (RTRRMS)

Introduction

Research has shown that surface roughness is one of the primary variables that drivers use to measure the quality of service provided by a pavement surface (Hudson 1981). The need to measure road roughness has led to the advent of numerous instruments. These systems range from simple devices to more complex systems (Sayers *et al.* 1986b). Today, road roughness is generally measured with high-speed profilometers. These instruments are relatively expensive and unlike response type devices, only a few network agencies and service providers can afford to purchase and maintain their own profiler (COTO 2007). These limitations circumvent the opportunity to measure a wider footprint of the road network on a continuous, real-time basis. Some of these limitations instigated the prospect of exploring other low-cost alternatives for this purpose. Hundreds and thousands of telematics devices are installed in vehicles throughout South Africa and the world and the majority of them are securely fitted to the body of the vehicles, thus making them an attractive option for obtaining relatively accurate information regarding the response of vehicles to road conditions. The cost-effectiveness of utilising data harvested from telematics device sensors also plays a governing role in the growing economy and can assist with bridging the gap between urgent needs that need to be addressed on roads, and the future evolution of transportation.

Related research

This section includes literature on road roughness, International Roughness Index (IRI) versus Half-car Roughness Index (HRI), IRI ranges, roughness measurement classes, calibration techniques for response type devices and existing low-cost solutions to assess road roughness.

Road roughness

According to the American Society of Testing and Materials (ASTM), the definition (E867) for road roughness is (ASTM International 2012):

> The deviations of a pavement surface from a true planar surface with characteristic dimensions that effect vehicle dynamic, ride quality, dynamic loads, and drainage, for example, longitudinal profile, transverse profile, and cross slope.

Roughness is not a point, but rather a summary of deviations that occur over an interval between two points (Sayers and Karamihas 1998).

IRI versus HRI

IRI is defined as a roughness index for a single wheel track profile, obtained by using a Quarter-Car model (Figure 1) with specific Golden Car vehicle parameter values. An associated roughness measure, known as the HRI can be obtained using both wheel track profiles as input to the same computer algorithm as for the IRI. This analysis is mathematically equivalent to a Half-Car model (Figure 2). IRI more closely indicates the vehicle response at the wheels, whereas HRI more closely indicates the response of the vehicle at its centre (Sayers 1989).

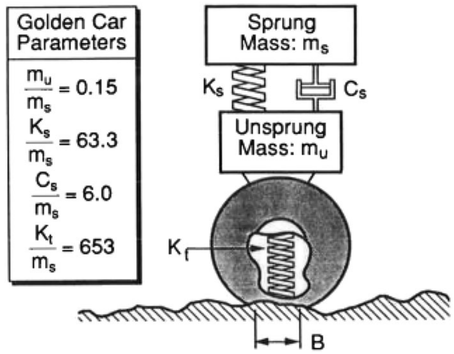

Figure 1. Quarter-car model (Sayers 1989).

IRI ranges

Typical IRI ranges for different road classes are shown in Figure 3, where the IRI scale ranges from 0 to 20 m/km. Recommended operating speeds that correspond to specific IRI ranges are also provided (Sayers and Karamihas 1998).

Roughness measurement classes

Roughness measurement methods were divided into four broad classifications based on how directly their measures pertain to the IRI, which in turn affects their calibration procedures as well as the accuracy of their associated use (Table 1) (Sayers *et al.* 1986b).

Calibration for response type device

The response behaviour of a Response Type Road Roughness Measuring System (RTRRMS) is unique and variable with time. The system should be calibrated when it is initially put into service and periodically throughout its use when its response falls outside the control limits. One method to calibrate a RTRRMS is to use control sections to perform calibration by correlation. Calibration is generally performed by running the RTRRMS over a number of control road sections of known roughness, obtained through concurrent measurement using a reference method. Measures obtained from the RTRRMS, in combination with the reference roughness numeric, are used to determine a regression equation that can be used to convert future RTRRMS measures to estimates of what the reference measure would have been (Sayers *et al.* 1986a). Tables 2 and 3 offer some guidelines that can be used to accept or reject a specific calibration by the correlation method followed.

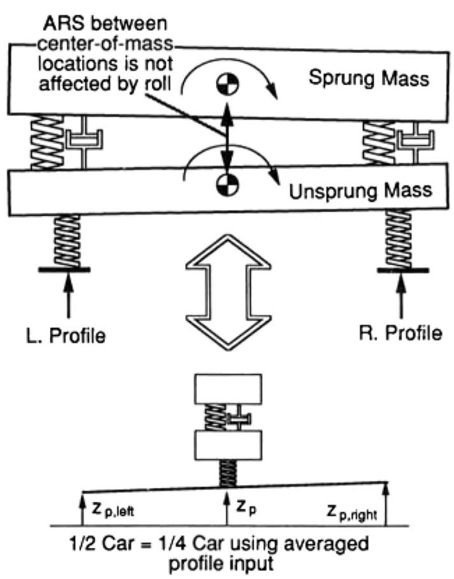

Figure 2. Half-car model (Sayers 1989).

Low-cost solutions to assess road conditions

Several low-cost solutions have been developed that utilises dedicated standalone sensors (Gregg and Foy 1955, Rizenbergs 1965, González *et al.* 2008, Chen *et al.* 2011, Lakušić *et al.* 2011, Tomiyama *et al.* 2012) or smartphone sensors (Pertunnen *et al.* 2011, Douangphachanh and Oneyama 2013, Hoffmann *et al.* 2013, Alessandroni *et al.* 2014, Belzowski and Cook 2014, Jones and Forslof 2014, Schlotjes *et al.* 2014, Bridgelall and Daleiden 2015) to monitor road conditions. In each of these solutions, different algorithms/approaches have been developed and evaluated for their appropriateness. Although smartphones have several advantages when it comes to measuring road conditions, some disadvantages, however, exist. Some of these disadvantages include virtual reorientation of the accelerometers, limited battery life of smartphones and the need for human, manual intervention to record the measurements. Telematics technology, therefore, seems to be a more attractive alternative to some of the current systems used. These advantages include the fact that telematics devices are already securely fastened to the body of vehicles, accelerometers of telematics devices are automatically aligned after installation (i.e. no need for manual alignment), telematics devices are powered by the vehicle and no human or manual intervention is

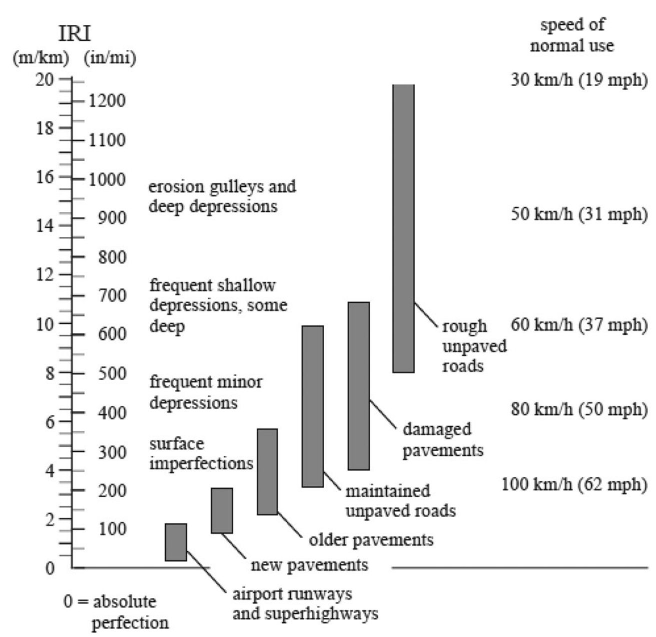

Figure 3. IRI ranges for different road classes (Sayers and Karamihas 1998).

Table 1. Classification of measurement classes and devices (Sayers *et al.* 1986b, ASTM E950-98 2004, COTO 2007).

Classes	Definition
Class 1: Precision profiles	Highest standard of accuracy and precision for measurement of the IRI Maximum longitudinal sampling interval: ≤ 25 mm Vertical resolution:≤ 0.1 mm
Class 2: Other profilometric methods (non-precision profiles)	Not the same accuracy and precision required as for Class 1 Maximum longitudinal sampling interval: 25 mm < and ≤ 150 mm Vertical resolution: 0.1 mm < and ≤ 0.2 mm
Class 3: IRI estimates from correlation equations (Response Type Road Roughness Measurement Systems (RTRRMS))	Estimate the IRI through regression equations if appropriate correlation experiments are performed Maximum longitudinal sampling interval: 150 mm ≤ and ≤ 300 mm Vertical resolution: 0.2 mm < and ≤ 0.5 mm
Class 4: Subjective ratings and uncalibrated measures	Roughness measurements have no verifiable link to the IRI scale (i.e. subjective evaluation) Maximum longitudinal sampling interval: > 300 mm Vertical resolution: > 0.5 mm

required to record the measurements (i.e. data are automatically recorded when a vehicle's ignition is switched on and off).

Methodology

The broad methodology that was followed to obtain the response-based road roughness measurements utilising data harvested from the telematics device sensors is discussed.

The typical telematics device used in this study is shown in Figure 4. These devices comprise of global positioning system (GPS), accelerometer and gyroscope sensors that make them suitable for measuring road condition. In this specific study only, the GPS and accelerometer sensors will be used.

The telematics device's spatial frame of reference is defined with respect to the vehicle's frame of reference as shown in Figure 5.

Benchmark road roughness measurements were obtained using Class 1 profilometers. A Mark III Road Surface Profiler (RSP) that is capable of offering data at a range of speeds as well as real-time linear chainage, survey speed, sub-meter

Table 2. Guidelines for calibration acceptance criteria (COTO 2007).

Parameter	Recommended criteria for application type: Lower reliability	Recommended criteria for application type: Higher reliability
Scatter plot showing IRI (Y-axis) versus measured parameter	Examine scatter plot and ensure that the relationship is linear and that the data range covers the range of expected IRI values on the network	
Coefficient of determination (R^2) for regression (Note 1)	Greater than 0.950	Greater than 0.975
Standard Error (SE) for regression	0.45	0.35

Note 1: Regression refers to simple regression analysis. For this regression, the dependent (Y) parameter is the reference IRI over each 100 m of the calibration section. The independent (X) parameter is the measured parameter over each 100 m segment, and for each repeat.

Table 3. Calibration requirements for response type devices (COTO 2007).

Parameter	Recommended requirements for application type (Note 1): Lower reliability	Recommended requirements for application type (Note 1): Higher reliability
Number of sites for each relevant roughness range (Note 2)	2	3
Minimum site length	200 m	200 m
Repeat runs per site	4	4

Note 1: Use requirements for a lower reliability assessment if the objectives of the survey is a once-off estimation of roughness to prioritise maintenance and rehabilitation work. Use the higher reliability requirements if the objective of the survey is to determine a relative indication of network deterioration over a time period.
Note 2: The ranges to be covered include only those ranges which may be encountered on the network to be surveyed.

GPS coordinates, longitudinal profiles IRI, Ride Number (RN), transverse profiles, rut depths, macro textures and road geometry (cross fall, curvature and gradient) was used (SRT 2017).

Schematic diagram of approach

The broad procedures that were followed to obtain the response-based road roughness estimates are shown in Figure 6. It should be noted that the data underwent four steps that include data acquisition, data transformation, data analysis and approach validation.

Data analysis

The data analysis phase contained the following methods that were used to obtain the response-based road roughness (HRI and Average IRI) measurements.

Coefficient of variation of vertical (Z) acceleration

Coefficient of Variation (CoV) is a dimensionless measure of dispersion and is typically defined as the ratio of the standard deviation to the mean of a distribution and is often represented as a percentage (Van As 2008). The advantages of it being dimensionless are that data from different datasets can be compared with each other more readily. The equation that was used to calculate the CoV of the vertical (z) acceleration can be

Figure 4. SkyTrax telematics device used in this study (Tracker Connect Pty Ltd 2017b).

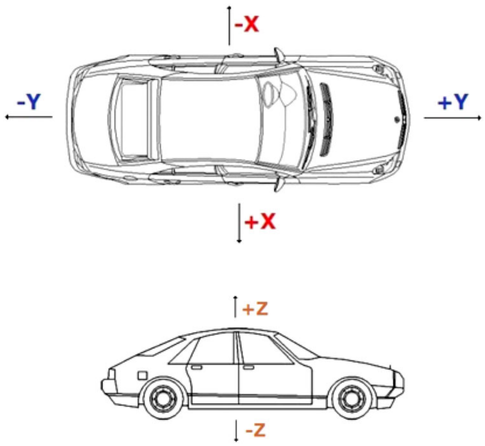

Figure 5. Accelerometer axes orientation of telematics devices (Tracker Connect Pty Ltd 2017a).

observed from Equation (1) (Van As 2008). In this paper, road roughness was estimated in 100-m segments to correspond with the general recommended distance to measure road roughness as stated in Table 2.

CoV of vertical (z) acceleration (Van As 2008):

$$\mathrm{CoV}_{a_z} = \frac{\sqrt{1/N\sum_{i=1}^{N}(a_{zi}-\mu_{a_{zi}})^2}}{1/N\sum_{i=1}^{N}a_{zi}} * 100, \tag{1}$$

for the 100-m road segment, where CoV_{a_z} is the CoV of the vertical (z) acceleration (in %), N is the number of acceleration points in a specific 100-m segment, a_{zi} is the specific vertical (z) acceleration point in a specific 100-m segment (in millig), g is the gravitational acceleration and $\mu_{a_{zi}}$ is the mean of the vertical (z) acceleration calculated for a specific 100-m segment (in millig).

Second-degree polynomial equations

Problems frequently arise in engineering and science where the dependent variable is a function of two or more independent variables (Blais 2010). In this study, it was confirmed that road roughness (i.e. HRI and Average IRI) is a function of the CoV of the vertical (z) acceleration and the average speed at which the vehicle travelled. It was determined that a second-degree polynomial equation achieved the best results compared to a third or higher degree polynomial equations which appeared to overfit the data. Additional research and the sampling of more road sections, however, would be performed to validate this. To generalise the data from a straight line to a second-degree polynomial equation, it can be explained by Equations (2) and (3) (Wolfram MathWorld 2017). Two separate second-degree polynomial equations were developed, one to estimate the HRI (Equation (2)) and one to estimate the Average IRI (Equation (3)).

Second-degree polynomial equation to estimate the HRI:

$$\begin{aligned} y_{\mathrm{HRI}} = & f(x_{\mathrm{CoV}}, x_{\mathrm{Speed}}) = a_0 + a_1 \cdot x_{\mathrm{CoV}} \\ & + a_2 \cdot x_{\mathrm{Speed}} + a_3 \cdot x_{\mathrm{CoV}} \cdot x_{\mathrm{Speed}} \\ & + a_4 \cdot (x_{\mathrm{CoV}})^2 + a_5 \cdot (x_{\mathrm{Speed}})^2, \end{aligned} \tag{2}$$

where y_{HRI} is the estimate HRI for a specific 100-m segment (in m/km), x_{CoV} is the CoV value calculated over a specific 100-m segment (in %), x_{Speed} is the average speed calculated over a specific 100-m segment (in km/h) and a_0, a_1, a_2, a_3, a_4 and a_5 are the scaling factors (coefficients) to estimate the HRI.

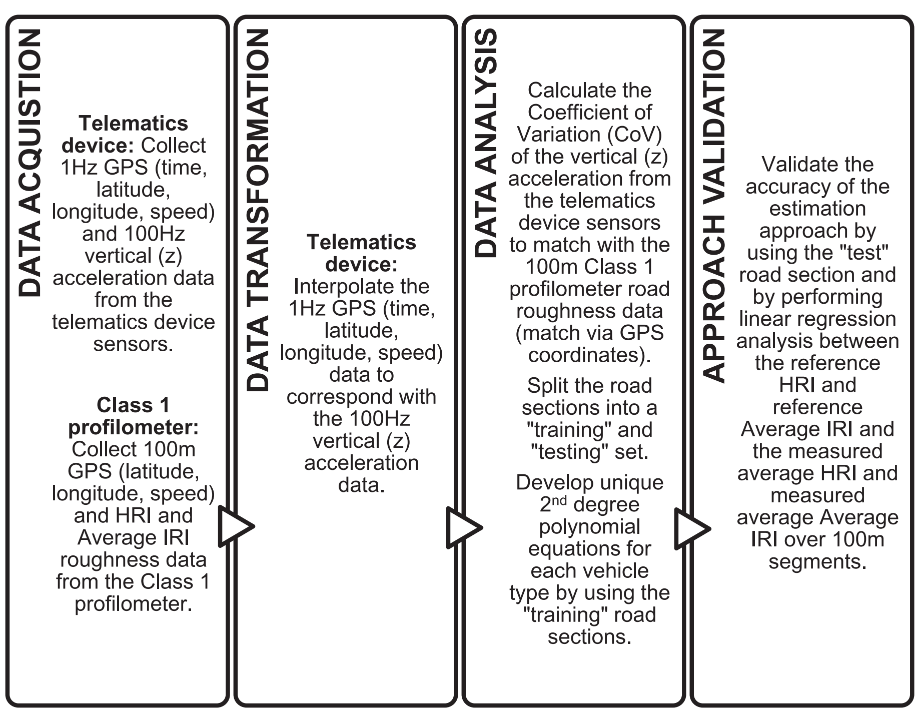

Figure 6. Schematic diagram of the response-based road roughness approach.

Second-degree polynomial equation to estimate the Average IRI:

$$y_{\text{AverageIRI}} = f(x_{\text{CoV}}, x_{\text{Speed}}) = b_0 + b_1 \cdot x_{\text{CoV}} + b_2 \cdot x_{\text{Speed}} + b_3 \cdot x_{\text{CoV}} \cdot x_{\text{Speed}} + b_4 \cdot (x_{\text{CoV}})^2 + b_5 \cdot (x_{\text{Speed}})^2, \quad (3)$$

where $Y_{\text{AverageIRI}}$ is the estimate average IRI for a specific 100-m segment (in m/km), x_{CoV} is the CoV value calculated over a specific 100-m segment (in %), x_{Speed} is the average speed calculated over a specific 100-m segment (in km/h) and b_0, b_1, b_2, b_3, b_4 and b_5 are the scaling factors (coefficients) to estimate the Average IRI.

Second-degree polynomial equations need to be developed for each vehicle type. To solve for the unknown scaling factors (coefficients) in Equations (2) and (3), Equations (4) and (5) were used (Wolfram MathWorld 2017).

Matrix equation for calculating the scaling factors (coefficients) of the second-degree polynomial used to estimate the HRI:

$$\hat{a} = (M_{\text{HRI}}^T \cdot M_{\text{HRI}})^{-1} \cdot M_{\text{HRI}}^T \cdot \hat{y}_{\text{HRI}}. \quad (4)$$

Matrix equation for calculating the scaling factors (coefficients) of the second-degree polynomial used to estimate the Average IRI:

$$\hat{b} = (M_{\text{AverageIRI}}^T \cdot M_{\text{AverageIRI}})^{-1} \cdot M_{\text{AverageIRI}}^T \cdot \hat{y}_{\text{AverageIRI}}. \quad (5)$$

Data collection

Data from five different road sections, of varying lengths and roughness' (as indicated in the cumulative distributions and box-and-whisker diagrams in Figures 7 and 8), and three different vehicle types (i.e. small hatchback, light delivery vehicle (LDV) and multi-purpose vehicle (MPV)) were collected. As response type devices are vehicle-dependent, these representative (of typical South African) vehicles were used. Each of the three different vehicle types travelled at seven different speeds (i.e. 30, 40, 50, 60, 70, 80 and 90 km/h) over each of the five road sections. A range of different speeds was selected due to the fact that it was evident that accelerometer data are sensitive to changes in speed and models should, therefore, be developed in order to remove bias towards varying speeds. The constant speeds were achieved by using the vehicles' cruise control functions. In order to demonstrate the feasibility of the specific approach followed and used, the five different road sections were split into a 'training' and 'test' set. This meaning that four of the road sections were used to obtain the second-degree polynomial equations for the three different vehicle types whereas one road section was used to test the accuracy of the particular estimation approach. From Figures 7 and 8, the condition of each of the 'training' road sections should be evident. It should be observed from the cumulative frequency distributions and box-and-whisker diagrams (Figures 7 and 8) that Road Section 2 has the best condition whereas Road Section 1 and Road Section 3 has the poorest condition.

Data analysis and results

In this section, the specific approach followed and adopted is critically analysed based on its reliability to estimate road roughness. This is done through linear regression analysis (LRA) between benchmark Class 1 road roughness data and the average measured response-based (similar to Class 3) road roughness data of an independent 'test' road section. It should be noted that this paper forms part of continuous research and that results (statistical indices discussed in this section) can be improved as more data are collected and more vehicle types are used to measure road roughness. This research forms part of a proof of concept and thus should be considered as such.

Linear regression analysis

In order to validate the practicality and accuracy of the particular approach, LRA was performed between the benchmark Class 1 HRI and Average IRI (Y dependent variables) and the average measured response-based (similar to Class 3) HRI and Average IRI (X independent variables) for the 'test' road section (Figures 9 and 10). These relationships were obtained by utilising the second LSPEs as developed from the 'training' road sections and applying it to the 'test' road section for each of the different vehicle types that travelled at the different speeds. The average result of the measured road roughness was compared with the benchmark road roughness.

Correlation coefficient

The correlation coefficient (R) is a single summary number that indicates how closely one variable is related to another, the direction of the relationship and how strong it is. A large R-value indicates linearity of the relationship ($-1.00 < R < 1.00$). An R-value of -1.00 indicates a perfect negative relationship between the two variables while an R-value of $+1.00$ indicates a perfect positive relationship between the variables. An R of 0.00 means that no relationship exists between the two variables (Ryan 2007, Van As 2008, Higgens 2010). The R calculated from LRA of the benchmark Class 1 HRI and average measured response-based HRI (Figure 9) is 0.87. The R calculated from LRA of the benchmark Class 1 Average IRI and the average measured response-based Average IRI (Figure 10) is 0.94. This indicates that a strong, positive linear relationship exists between the two variables.

Coefficient of determination

Coefficient of determination (R^2) represents the variability in Y that is explained by using X to predict Y. It is bounded by $0.00 \leq R^2 \leq 1.00$. An R^2 value near 1.00 indicates a good fit while a value near 0.00 indicates a poor fit (Montgomery and Runger 2006, Ryan 2007, Van As 2008, Ross 2009, Higgens 2010). The adjusted R^2 calculated from LRA of the benchmark Class 1 HRI and average measured response-based HRI (Figure 9) is 0.75, while the R^2 calculated from LRA of the benchmark Class 1 Average IRI and average measured

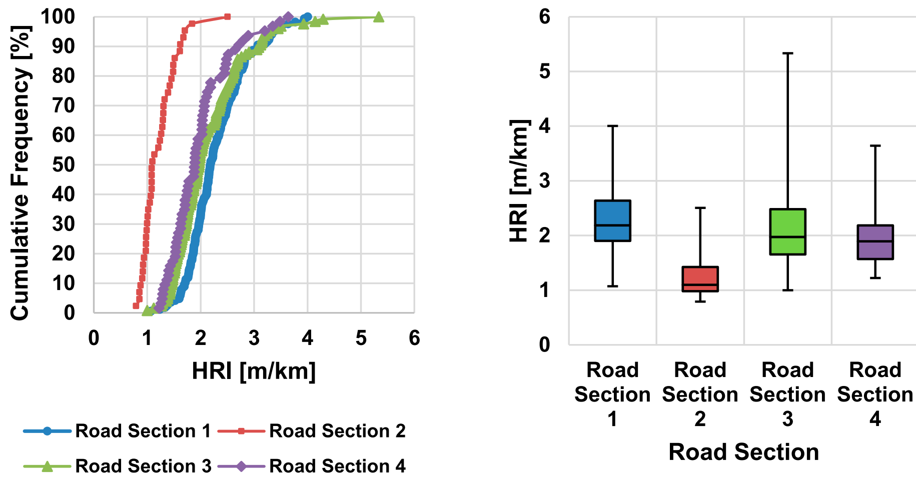

Figure 7. Cumulative frequency distributions and box-and-whisker diagrams of the HRI for the four 'training' road sections.

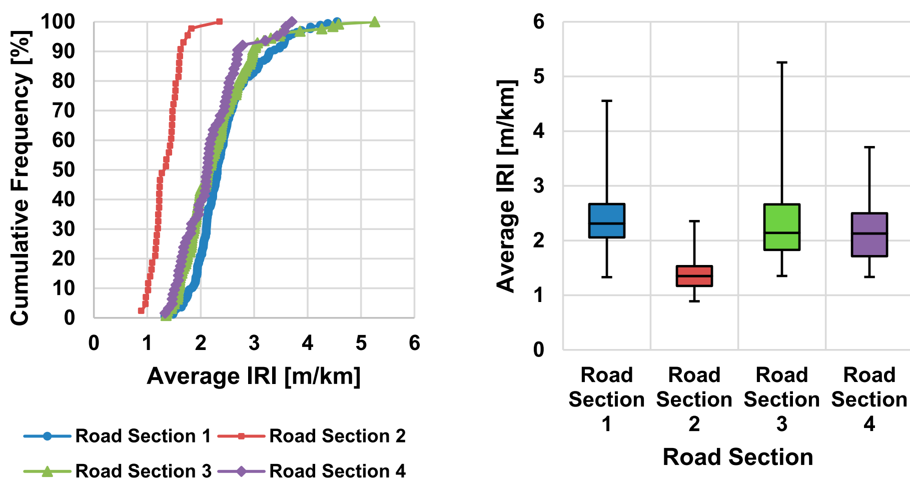

Figure 8. Cumulative frequency distributions and box-and-whisker diagrams of the Average IRI for the four 'training' road sections.

response-based Average IRI (Figure 10) is 0.88. This indicates that both lie closer to 1.00, indicating a good fit between the two variables.

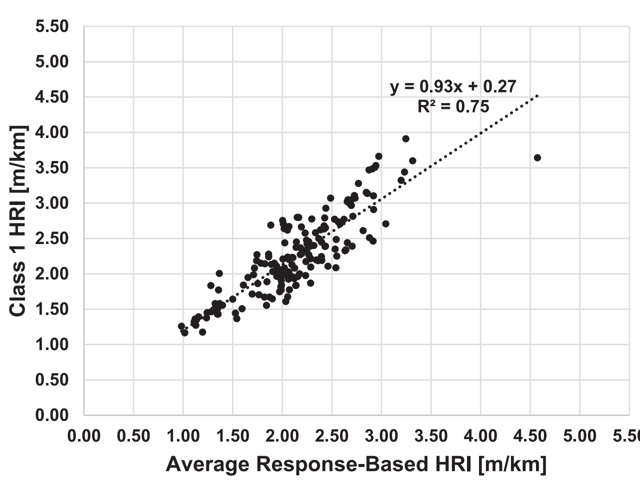

Figure 9. LRA between the benchmark HRI and the average measured HRI for the 'test' road section.

Standard error of the estimate

The Standard Error (SE) of the estimate is the standard deviation of a distribution. The SE is a single summary number that indicates how accurate the predictions are when linear

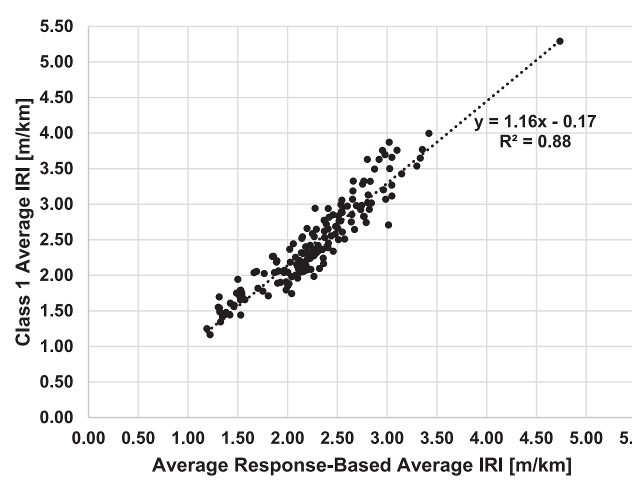

Figure 10. LRA between the benchmark Average IRI and the average measured Average IRI for the 'test' road section.

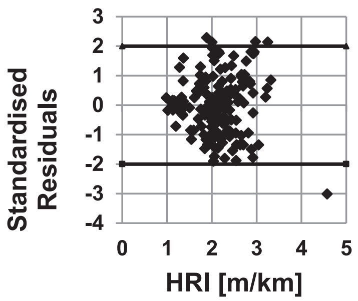

Figure 11. Standardised residual values for the HRI.

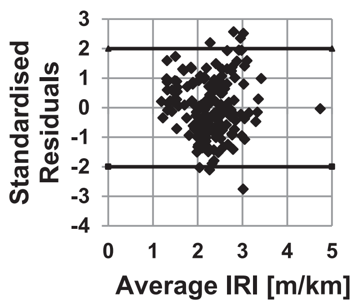

Figure 12. Standardised residual values for the Average IRI.

regression is performed, with smaller SE-values indicating higher accuracy (Higgens 2010). SE calculated from LRA of the benchmark Class 1 HRI and average measured response-based HRI (Figure 9) is 0.29. SE calculated from the LRA of the benchmark Class 1 Average IRI and average measured response-based Average IRI (Figure 10) is 0.22. After comparing these SEs with the acceptable SEs for high reliability listed in Table 2, it should be noted that they both fall within the range to be accepted with high reliability.

Residuals analysis

Residuals are helpful in examining the assumption that errors are approximately normally distributed with a constant variance. They also help to determine whether additional terms are required in the model. If errors are normally distributed, approximately 95% of the standardised residuals should fall in the interval (−2, +2). Residuals that fall far outside this interval may indicate the presence of outliers (Montgomery and Runger 2006). Comparing the standardised residual value limits (Figures 11 and 12) with the limits stated above, it should be evident that 95% of the standardised residual values lie within the range of (−2, 2), and thus the stated procedure used to obtain the measured response-based road roughness (HRI and Average IRI) can be accepted with confidence.

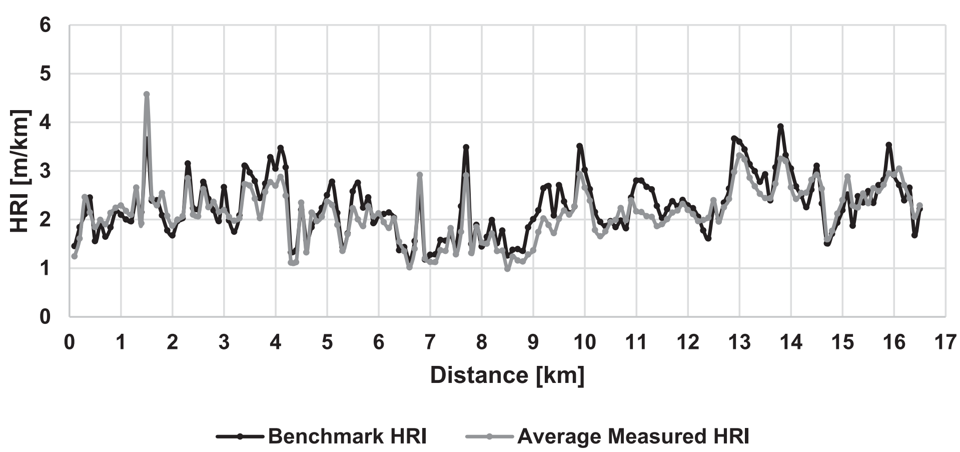

Figure 13. Benchmark HRI and the average measured HRI for the 'test' road section.

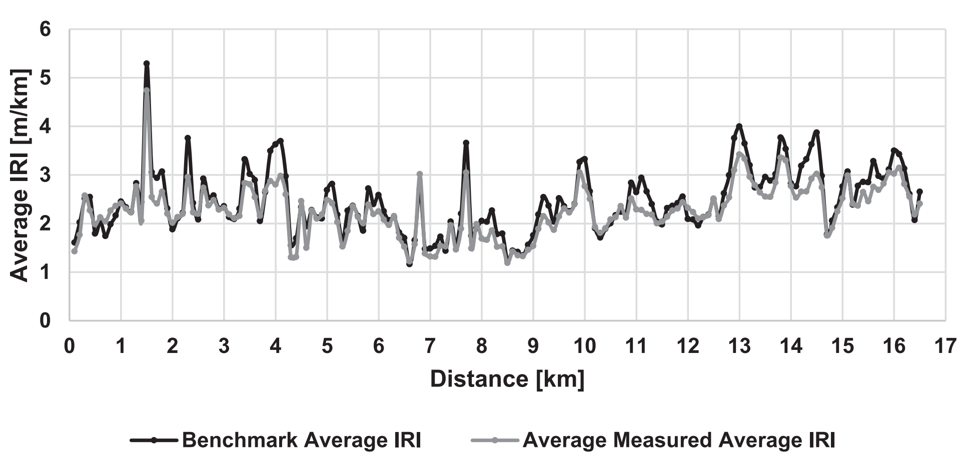

Figure 14. Benchmark Average IRI and the average measured Average IRI for the 'test' road section.

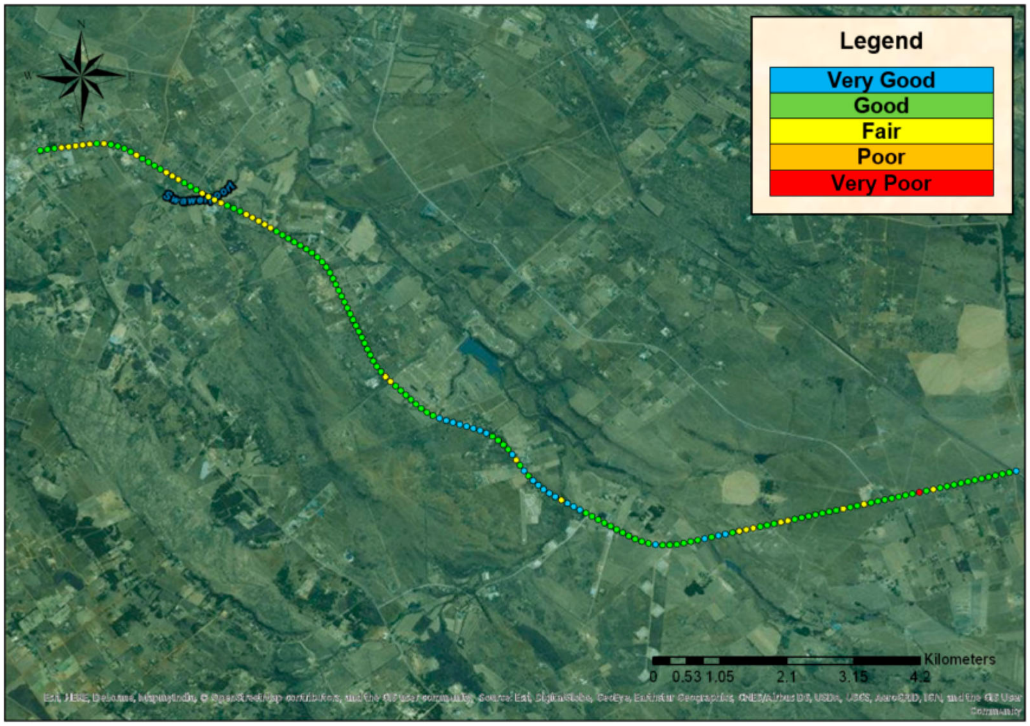

Figure 15. Measured response-based HRI (ArcGIS Pro 2017).

Table 4. Condition ranges used for visualisation of road roughness data.

Condition	HRI (m/km)	Average IRI (m/km)
Very good	0.00–1.50	0.00–1.50
Good	1.50–2.60	1.50–2.60
Fair	2.60–3.50	2.60–3.50
Poor	3.50–4.20	3.50–4.20
Very poor	4.20–20.00	4.20–20.00

Benchmark road roughness versus average measured road roughness

The benchmark (Class 1) road roughness (HRI and Average IRI) and average measured response-based (similar to Class 3) road roughness (HRI and Average IRI) values, calculated for the 'test' road section, were plotted on the same set of

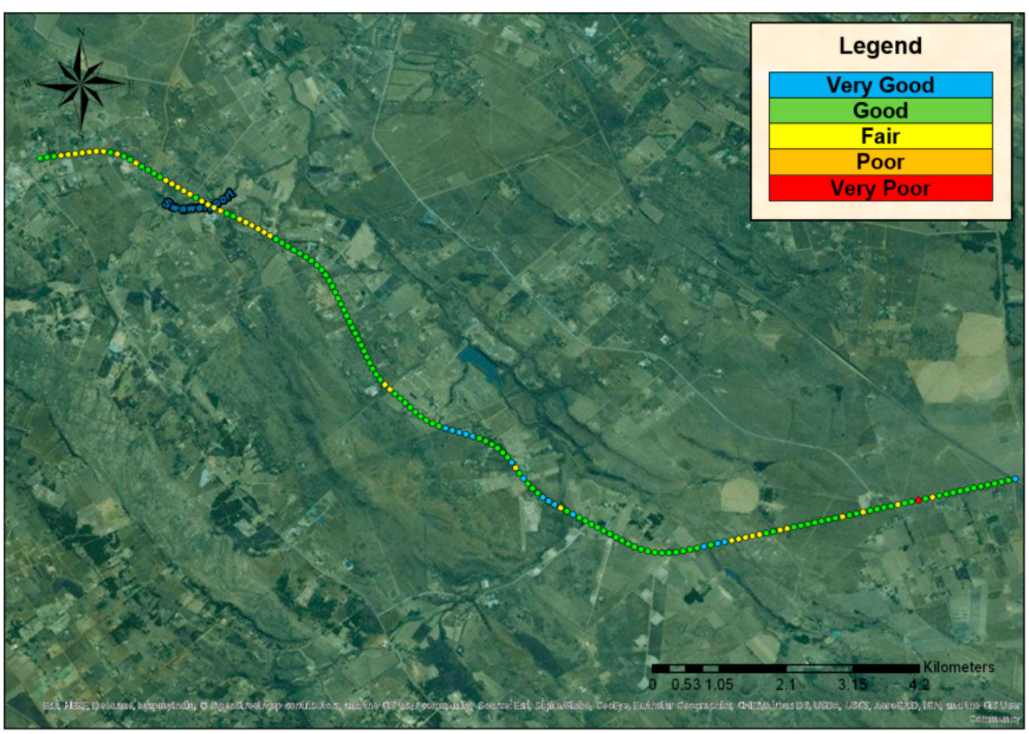

Figure 16. Measured response-based Average IRI (ArcGIS Pro 2017).

axes (Figures 13 and 14) in order to indicate the close relationship that exist between them. From Figures 13 and 14, it should be evident that the trends for the road roughness profile remain more or less similar and that little deviation exists between them.

Visualisation of the Class 3 road roughness

Road condition was visualised using a mapping application that shows the road condition using five primary colours, primarily for a road in a very good, good, fair, poor and very poor condition (Figures 15 and 16). The condition ranges used, were selected based on those as shown in Figure 3, with the ranges and their corresponding condition and colour shown in Table 4.

Conclusions

In this paper, it should be evident that relatively accurate response-based (similar to Class 3) road roughness indices can be obtained by utilising the data harvested from telematics device sensors in the field. This can be achieved by combining both statistics and matrix algebra and by performing appropriate 'calibration by correlation' procedures. Although this research shows major potential and can possibly disrupt some of the traditional methods being used, there still exist some room for improvement of which some include measuring the road roughness of more road sections as well as performing cross-correlation between repeat measurements. Road roughness data obtained from telematics devices can be utilised as 'screening' devices and assist with successfully closing the gap between Class 1, Class 2 and Class 4 measurement devices.

Future developments

Some of the future developments of this project include:

- Develop road deterioration rate models for different road sections by monitoring the continuous response-based (similar to Class 3) road roughness measurements over a period of time;
- Develop route optimisation models by categorising routes based on their distance and riding quality;
- Develop fuel consumption models (Rands/km) by incorporating the estimated road roughness data measured, and
- Develop agricultural goods loss models (Rands/km) when the conditions of roads are in a poor condition.

Disclaimer

This article reflects the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the company or the funders.

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