TELEMATICS-BASED TECHNOLOGY AND THE DEVELOPMENT OF ROAD CONDITION TRENDS FROM CLOUD-SOURCED DATA

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ABSTRACT

Road related telematics encompasses a combination of road transportation, in-vehicle electronics and telecommunications. It is continuously evolving in terms of complexity and diversity, and contains high volumes of sensor data. Telematics-based technology is mainly used for the recovery of hijacked/stolen vehicles, insurance purposes and vehicle fleet monitoring and management. In this paper, it is demonstrated that telematics-based technology may offer capabilities in terms of predicting road condition. This is based on a project where some simple statistical analysis techniques were used to interpret existing data originating from standard vehicle telematics units. The paper mainly evaluates the z-direction (up / down) acceleration for a few different vehicle types and x-direction (lateral), y-direction (longitudinal) and z-direction acceleration for the identification of road anomalies/defects. Roads are currently monitored using Class 1 profilometers, which provides a detailed but relatively costly indication of road condition. The use of vehicle telematics may provide a more cost-effective solution to monitor a wider road network and on a continuous basis, albeit on a Class 3 profilometer level. Telematics units are currently installed in numerous vehicle types throughout South Africa, and this paper focuses on achieving a reliable Class 3, real-time response-type measurement which can be used as a screening device and which is able to accurately produce an indication of road roughness, as well as major road distresses. This may assist in ensuring that agencies without direct access to funding for Class 1 road condition data may be able to obtain an indication of their road network conditions. It also contributes towards the safety and comfort of road users.

1. INTRODUCTION

Employment of proper maintenance and management strategies of roads require regular monitoring of the roads. This becomes particularly important for road conditions which may change in the short term (i.e. the sudden formation of a pothole, constant roughness changes in gravel roads etc.). The advancement of telematics-based technology has allowed the conditions of roads to be monitored through various vehicle-pavement interaction approaches. This technology allows roads to be monitored on a continuous, real-time basis by extracting the aggregated data obtained from the various on-board devices installed in the field. Similar applications exist which allows roads to be monitored via the smartphone platform (Koichi, 2013; Mohan et al, 2008; Roadroid, 2013; Schlotjes et al, 2014). Although these applications are not of the same level of accuracy and precision as Class 1 profilometers, it can potentially be used as screening devices to detect changes in the road condition over a more extensive road network, as they typically adhere to Class 3 road roughness measurement classifications. The objective of this paper is to illustrate that telematics-based technology can be utilised to monitor and predict the condition of the road. The data are harvested from a unique type of telematics device manufactured and installed into vehicles by the telematics company used in this study.

Road roughness measuring standards

The need to measure road roughness has led to the advent of various instruments. These instruments vary from Response-Type Road Roughness Measurement Systems (RTRRMS) to more sophisticated and dedicated profilometers. The main challenge of these instruments is calibration and correlation to a common scale of interest. This exists due to the variability present between the instruments utilised and the measurements recorded (Sayers and Karamihas, 1998).

The introduction of different measuring standards originated from the need for correlating and calibrating measurements and instruments. These include the Present Serviceability Index (PSI) and International Roughness Index (IRI), of which IRI is the international standard. Road roughness is characterised by the longitudinal profile of a road. It is always determined over a specified length of road and is defined as the ratio of the variation distance (or accumulated suspension motion of the vehicle) over a fixed distance travelled and has units of slope (m/km). The IRI statistic is a roughness index that is reproducible, portable and constant over time (Sayers and Karamihas, 1998; Jooste, 2007).

Measurement classes

Different measurement classes originated due to the various methods of operation, the reproducibility of the measurements and degree of accuracy and precision of the measurements (Jooste, 2007). The main classes of roughness measurements are shown in Table 1.

Table 1 Measurement classes to explain the accuracy and precision of roughness measurements (Jooste, 2007).

Class 1	Devices that measure a road profile with the highest degree of accuracy and precision. Maximum longitudinal sampling interval ≤ 25 mm. Precision of the vertical elevation measures ≤ 0.1 mm.
Class 2	Devices that can measure a road profile accurately. The standard accuracy of a Class 1 measurement is not attainable. Maximum longitudinal sampling interval > 25 mm and ≤ 150 mm. Precision of the vertical elevation measures > 0.1 mm and ≤ 0.2 mm.
Class 3	Response-type devices by which the measurements were calibrated by relating the measurements obtained to known IRI values on particular road sections. Maximum longitudinal sampling interval > 150 mm and ≤ 300 mm. Precision of the vertical elevation measures > 0.2 mm and ≤ 0.5 mm.
Class 4	Devices are not calibrated and include subjective ratings of road roughness. The measurements are not suitable for network level surveillance. Maximum longitudinal sampling interval > 300 mm. Precision of the vertical elevation measures > 0.5 mm.

Response-Type Road Roughness Measurement Systems (RTRRMS) (Class 3)
RTRRMS utilises the response of a vehicle to a specific road as an indication of road roughness. Several aspects need to be considered and calibrated correctly when using response-type measurements, and include tyre type, tyre inflation pressure, suspension system of the vehicle, vehicle dimensions, and the load and speed at which the vehicle travels during the time of measurement. When calibrated correctly, RTRRMS have proven to yield realistic estimates of road roughness (Sayers et al, 1986).

Telematics-based technology
The need for developing reliable Class 3 instruments to monitor roads on a continuous basis and roads of a lower strategic nature (i.e. remote areas) has led to the introduction of using telematics-based technology for this purpose. It is imperative that such technology (as for all other RTRRMS) is well-calibrated and the procedure understood clearly before application.

The process by which observations are made at a remote location and communicated wirelessly to receiving equipment for monitoring is known as telemetry (Merriam-Webster Dictionary, 2014). The advent of radio communication spawned an industry of telemetry systems. The first telemetry systems utilised analogue radio communication to transmit information. Limitations of these systems included limited bandwidth to transmit information, were very expensive, and applications were mostly of a military nature. The introduction of digital communication systems encouraged the development of telemetry systems. Cellular communication as a form of digital communication made it possible for suppliers to produce telemetry systems at a lower cost and this allowed the technology to be rolled out across a wide field of applications. The automotive industry is one such field which have benefitted from this development. Automotive telemetry systems, also known as telematics systems, utilise a wide range of sensors in the vehicle to observe vehicle location and behaviour to communicate the information via the cellular network to a central processing centre (Tracker Connect, 2014).

In the project that this paper is based on, use is made of data generated by telematics units installed by a South African vehicle tracking company that typically use these devices for the recovery of hijacked/stolen vehicles, insurance purposes and for monitoring and management of vehicle fleets.

Benefits and limitations of telematics technology
Telematics technology has built-in accelerometers that enable the vehicles in which they are installed to be used as a type of RTRRMS. Proper calibration of the measurements has the potential of producing Class 3 equivalent RTRRMS data. Telematics technology offers various benefits relating to measuring the condition of the road and includes:

- It is a relatively economical solution for monitoring the condition of the road network and reasonably inexpensive to operate and maintain. Algorithms can be developed to mine data of interest and virtual triggers can be placed on road sections over the air to detect vehicles which travel on a specific road;
- Telematics devices in the field are installed in secure locations for hijack/theft and or insurance purposes, thus minimum maintenance of the telematics devices are required. Algorithms exist which automatically orientate the telematics devices depending on how they have been installed in the vehicle;
- The technology can be used to measure roughness of unpaved roads as no laser detection are involved, and

- Telematics companies typically have large vehicle fleets which increases the data density (i.e. the company involved in the project that this paper is based on has a current fleet of approximately 260 000 of the specific brand of telematics device used in this study throughout South Africa). Thus it is possible to monitor a larger footprint of the road network and on a regular basis.

Telematics technology has limitations in terms of road condition monitoring and includes:
- It is a type of RTRRMS with all its typical RTRRMS limitations (i.e. tyre inflation pressure, type of suspension system, vehicle dimensions, vehicle load, vehicle speed etc.);
- Variations in the profiles measured depending on the vehicle type and the drivers who operate them, and
- The telematics devices are installed at different locations in each vehicle, thus small drifts in the measurements may be anticipated, and

The application of the technology is based on the principle of large datasets, thus smaller differences should originate between individual vehicles when executing a statistical analysis of a large dataset.

Components of the telematics device
Knowledge of the various different components of the telematics device is necessary before data of interest can be extracted. A prototype of the latest telematics device used for this study is shown in Figure 1.

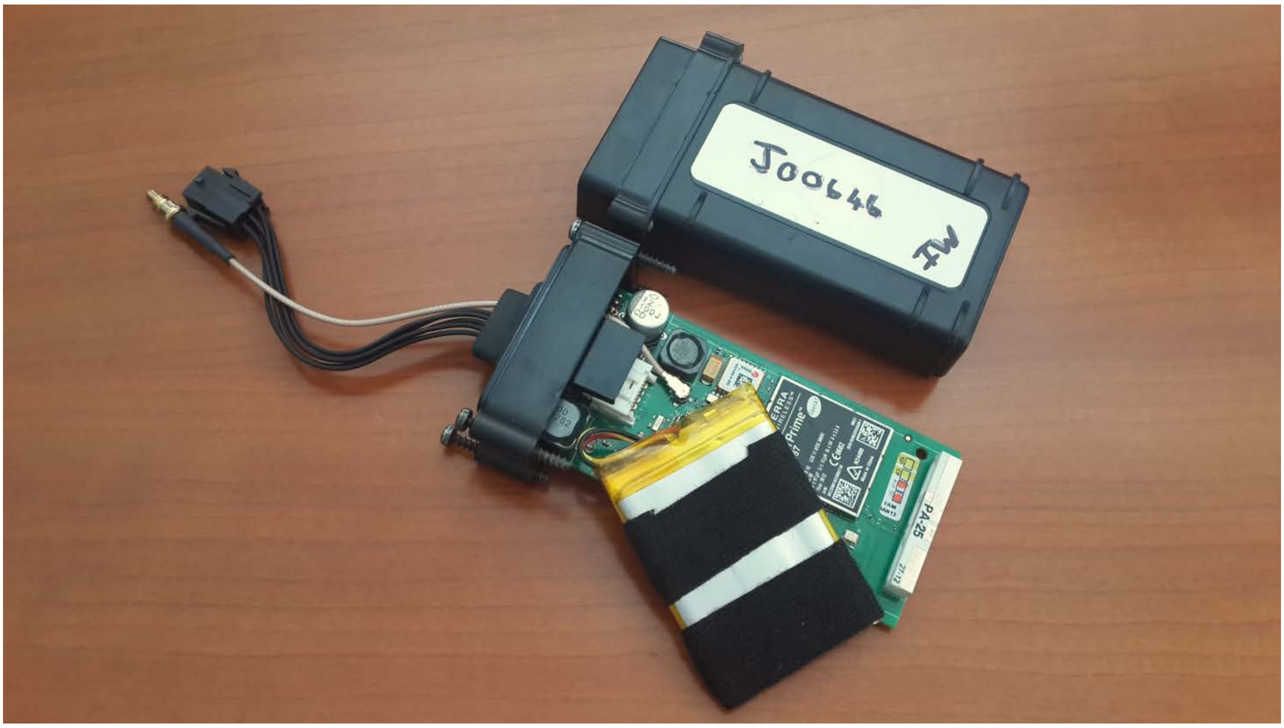

Figure 1 Telematics device used in this study (sourced from the company supporting the research).

The telematics device has the following major components:

- Battery - aids as backup for when the vehicle cannot supply the telematics device with power;
- Accelerometer - capable of measuring orthogonal acceleration. Firmware is used that automatically orientate the telematics device;
- Gyroscope - capable of measuring orthogonal rotational angular momentum. The gyroscope was not used in the current study, and
- Data storage locator – standard solid state data cards can be used on the units, although data are typically shared wirelessly to the host station.

The telematics device also has a built-in Global Positioning System (GPS) device that provides latitude and longitude of the vehicle to an accuracy of approximately 2.5 m Circular Error Probability (CEP). The location of the vehicle is communicated to a Monitoring Centre via Global System for Mobile (GSM) Communications (Tracker Connect, 2014). The speed at which the vehicle travels is also derived from the GPS.

Calibration of the telematics device

Appropriate calibration techniques need to be applied before measurements can be logged. Calibration involves eliminating “noise” and producing data which is of value or interest (Sayers and Karamihas, 1998). It should be noted that the response behaviour that a specific RTRRMS produces is unique and variable with time, thus proper calibration methods should be employed initially during testing and in-service and intermittently throughout use (Sayers et al, 1986).

Due to this research study still being in its early stages, a suitable starting data sampling rate for the telematics devices were required. An initial sampling rate of 100 Hz was selected as it relates to a measurement of road roughness every 278 mm for a typical vehicle travelling at a speed of 100 km/h (Tracker Connect, 2014). This relates well to a standard IRI data filter of 250 mm (Sayers and Karamihas, 1998).

The intent of this paper is partly to indicate how the data responses from the telematics units are used with real profile data to conduct calibration of the cloud of available vehicles.

Location of the telematics device

The location of the telematics device in the vehicle may affect the results attained. This is due to some telematics devices picking up mostly the bounce of a vehicle and not the roll component. This predominantly arises if the telematics device is installed in the centre of the vehicle than closer to a wheel path. In the field, each vehicle has at least one tracking device installed at a strategic location by the vehicle telematics company used for this study.

An illustration of the orientation of the telematics device accelerometer measurements is shown in Figure 2.

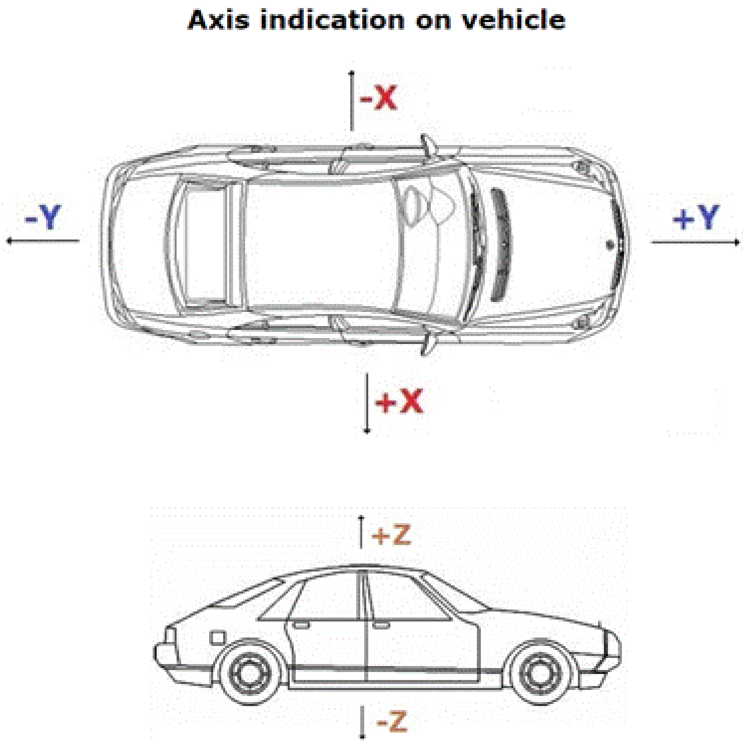

Figure 2 Acceleration axes of telematics device (sourced from the company supporting the research).

2. APPLICATION OF VERTICAL ACCELERATION IN DETERMINING ROAD CONDITIONS

The RTRRMS data were only evaluated for a limited number of typical South African passenger vehicles. The vehicles used in this study comprised of a small hatchback, a large hatchback, a Light Delivery Vehicle (LDV), and a large Sport Utility Vehicle (SUV). These four vehicles were driven over a specific section of road at four different speeds (i.e. 40 km/h, 60 km/h, 80 km/h and varying speed). The constant speeds were controlled using the vehicles cruise control systems. The tyre inflation pressures were set at the manufacturers recommended values before the tests were conducted. The telematics devices were all installed at different locations in each vehicle - each telematics device were either installed close to a front or rear wheel.

Acceleration (z-direction)

The z-direction acceleration of all the vehicles was evaluated against distance. The average z-direction acceleration data for the different vehicles on the same section of road are shown in Figure 3. From the raw acceleration (z-direction) data in Figure 3, noticeable problem areas for the road section should be evident. This can be seen where there are acceleration peaks in the z-direction for each vehicle type at the different vehicle speeds.

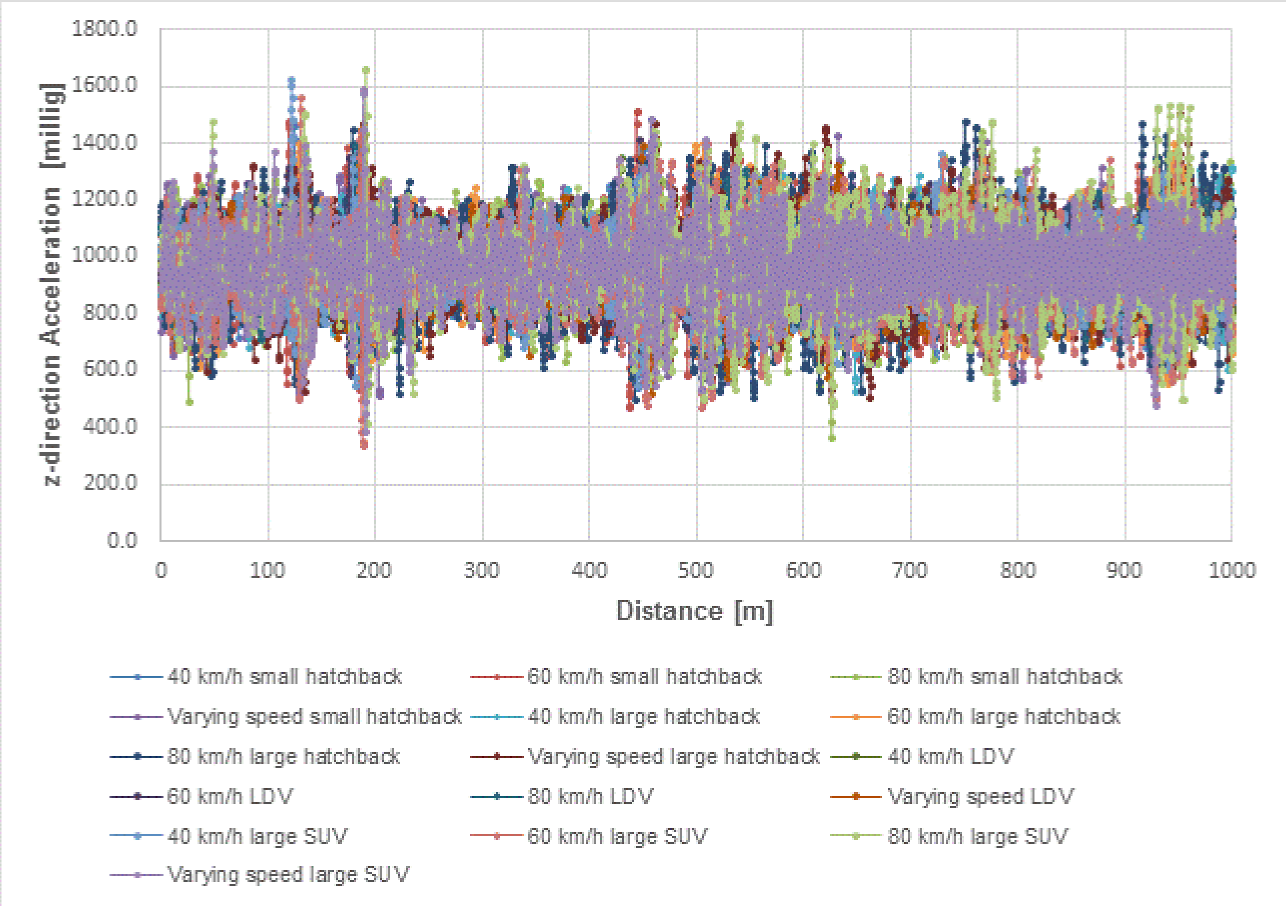

Figure 3 z-direction Acceleration versus distance of different vehicles at different speeds.

Coefficient of Variation (CoV)

The CoV is a dimensionless quantity of dispersion. It is often used to measure the variability or dispersion of data in relation to the mean of a distribution. It is more simply defined as the ratio of the standard deviation to the mean of the data (Van As and Joubert, 2008). The CoV values of the z-direction acceleration for each 10 m increment were calculated and are shown in Figure 4. The dimensionless property of the CoV allows data from different vehicles to be compared more readily. Similarity between the trends of different CoV data plots generated is noticeable in Figure 4. Areas of high CoV values can be associated to areas of high road roughness (refer to the areas indicated by the red circles in Figure 4).

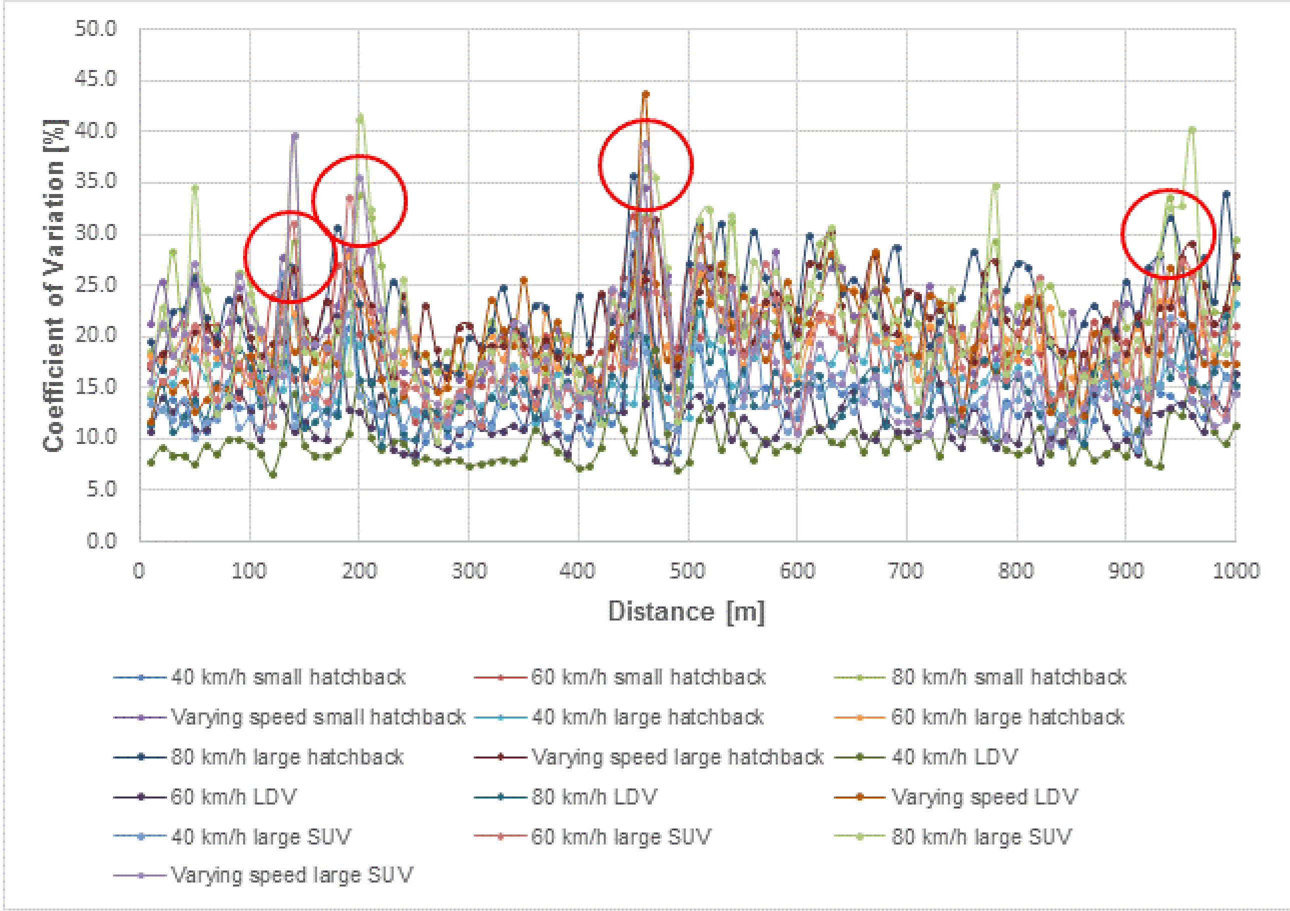

Figure 4 CoV versus distance of different vehicles at different speeds.

Normalised Coefficient of Variation (CoV)

From Figure 4 it is evident that variable speeds and vehicle type has an effect on the results attained, and thus the CoV data still portrays vertical scatter, although the trends for the road section portrays similar outputs. The data output shown in Figure 4 can be viewed as a standard first order data set that can be obtained from a cloud of data collected from vehicles fitted with telematics devices.

To remove the vertical scatter, the CoV data were normalised for each vehicle (Figure 5). This was achieved by dividing each CoV value for each vehicle type by the average CoV obtained for that specific vehicle over the specified road section. This effectively minimises the effects of vehicle type, tyre type, tyre inflation pressure, load of the vehicle, position of the telematics device in the vehicle, and varying speed in order to achieve better results for further analysis. The data in Figure 5 can also be perceived as a distribution, which is expected to be unique for roads with different roughness and anomalies. Analysis of the data of a larger vehicle fleet forms part of the current phase of this research.

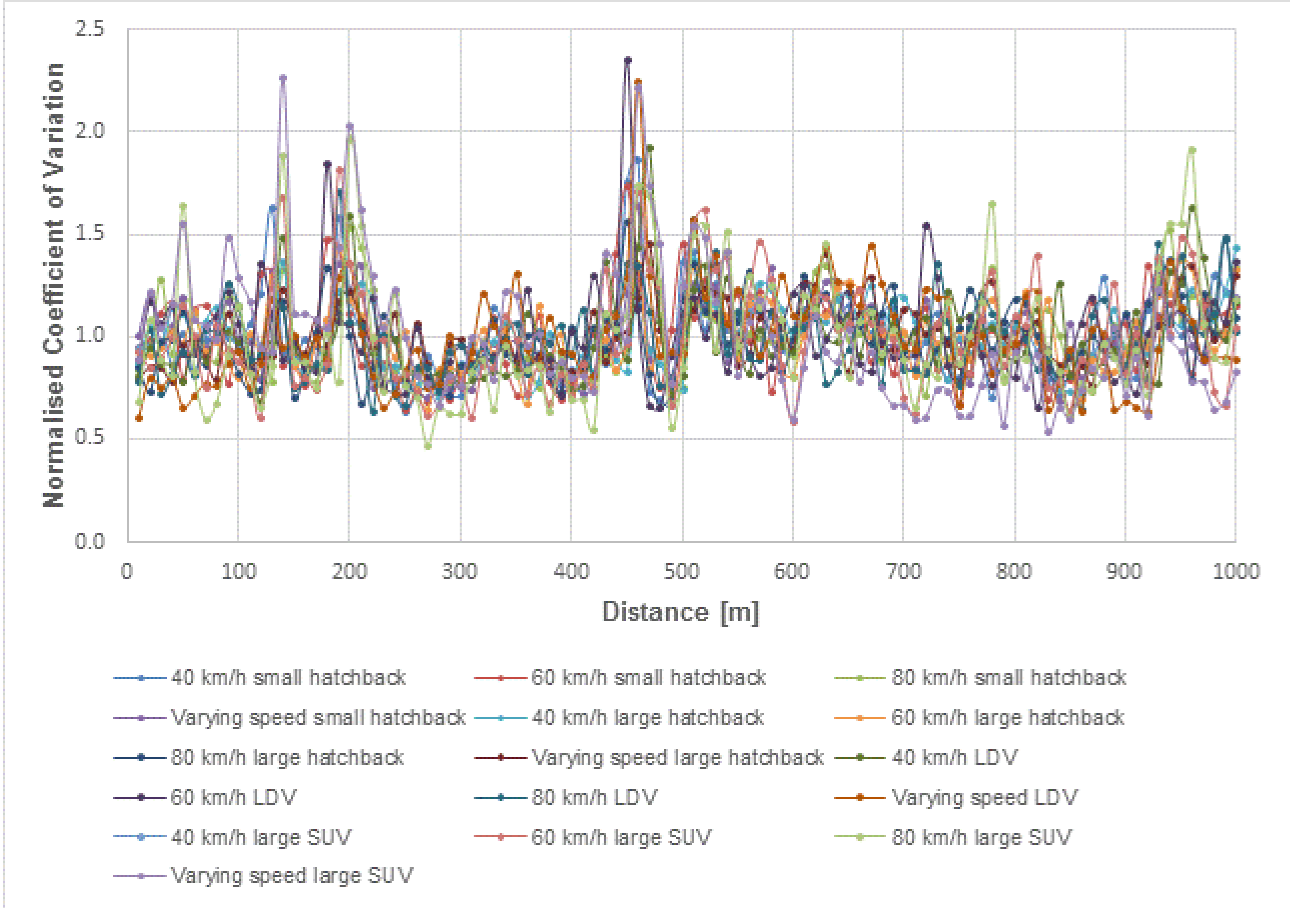

Figure 5 Normalised CoV versus distance of different vehicles at different speeds.

Relationship between telematics-based data and Class 1 profilometer data

The accuracy of the telematics-based RTRRMS data can be investigated by correlating the combined RTRRMS data from the telematics devices with the Class 1 profilometer data of the road section measured. The Half-car Roughness Index (HRI) of the profilometer data was used to determine a relationship between the two sets of data. The HRI is an IRI algorithm which determines the average of profiles (Sayers and Karamihas, 1998). It was decided to use the HRI for comparison with the RTRRMS data from the telematics devices as the telematics devices monitors the movement of the body of the vehicle and not of an individual tyre in a specific wheel path.

No further calibration or normalisation of the profilometer data is required as it is already a statistical representation of the road profile. Thus, the normalised CoV of the acceleration (z-direction) data was directly compared to the HRI for 10 m segments of the road section. The relationship obtained between these two variables is shown in Figure 6. The linear relationship improves if a larger sample size of vehicles is used for analysis.

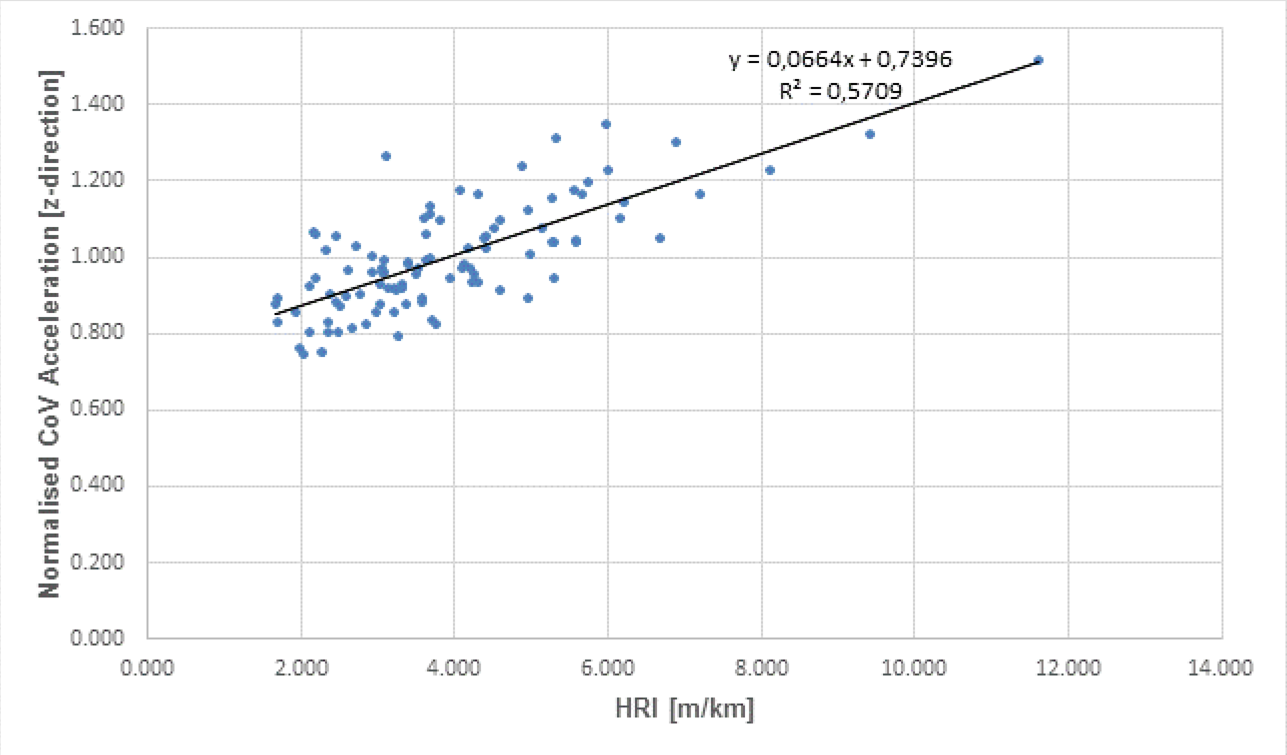

Figure 6 Linear regression of normalised CoV and HRI

Linear regression of normalised CoV and HRI

A linear regression analysis was performed for the normalised CoV for each vehicle at the four different speeds against the actual measured HRI of the section of road. From the regression analysis performed the coefficient of determination (R^2), correlation coefficient (R) and the standard error were calculated. A confidence interval provides a measure of the accurateness, or ambiguity of the data collected for analysis. A confidence interval of 95 per cent was selected for analysis as it was assumed that 95 per cent of the values are representative of the population mean (Montgomery and Runger, 2007).

Correlation coefficient (R)

The correlation coefficient is a method of indicating how strong a linear relationship is. It measures the degree to which two variables are linearly related (Montgomery and Runger, 2007). From Table 2 it should be observed that the relationship between the normalised CoV and the actual HRI of the section of road for all the vehicles combined is relatively strong. Thus, it can be said that the larger the sample size of vehicles used, the more accurate results can be obtained. Different vehicles produce different correlation coefficients at different speeds, and thus it is advised to use a larger sample size of vehicles to reduce the probability of errors from occurring. The correlation coefficient (R) for all the vehicles and speeds combined is 0.756. Errors can occur in the results attained (i.e. the telematics devices are all installed in different locations in each vehicle, all the vehicles did not travel in the same wheel path, the GPS coordinates does not overlap exactly and errors can arise from drifts in the electronic components etc.).

Table 2 Correlation coefficients (R) of normalised CoV and HRI

	Speed [km/h]			
Vehicle	**40**	**60**	**80**	**Varying**
Small Hatchback	0.707	0.531	0.419	0.681
Large Hatchback	0.336	0.542	0.491	0.374
Light Delivery Vehicle	0.373	0.261	0.576	0.612
Large Sport Utility Vehicle	0.648	0.574	0.414	0.395
Vehicles Combined	**0.749**	**0.696**	**0.608**	**0.684**

Standard error

The standard error is also known as the standard deviation of the sampling distribution of a statistic. The standard error is inversely proportional to the size of a sample (Montgomery and Runger, 2007; Investopedia, 2015). The standard error should become smaller if the sample size increases. From Table 3 it should be evident that the accuracy of the data improves if the sample size of vehicles used increases (i.e. the standard error becomes much smaller for a combination of vehicles).

Table 3 Standard error of normalised CoV and HRI

	Speed [km/h]			
Vehicle	**40**	**60**	**80**	**Varying**
Small Hatchback	0.155	0.176	0.180	0.133
Large Hatchback	0.153	0.143	0.164	0.152
Light Delivery Vehicle	0.196	0.228	0.167	0.199
Large Sport Utility Vehicle	0.179	0.223	0.298	0.310
Vehicles Combined	**0.097**	**0.113**	**0.138**	**0.124**

From the linear regression model generated in this paper, approximate normalised CoV ranges for road roughness can be computed. The IRI ranges are ranges which currently forms part of the standard roughness categorisation of roads in South Africa. More accurate ranges for the normalised CoV ranges can be obtained if more and better calibration techniques are employed to the data and if a larger sample size of vehicles is used for analysis.

Table 4 Standard roughness IRI categorisation ranges and approximate normalised CoV ranges

	IRI Range [m/km]	**Approximate Normalised CoV Range**
Very Good Condition	0 to 1.5	0 to 0.84
Good Condition	1.5 to 2.2	0.84 to 0.89
Fair Condition	2.2 to 3.0	0.89 to 0.94
Poor Condition	3.0 to 4.2	0.94 to 1.02
Very Poor Condition	4.2 -	1.02 -

3. ROAD ANOMALY DETECTION

The response of the vehicle (and thus the installed telematics device) when travelling over road anomalies such as potholes, speed-bumps and untrue bridge-deck joints can potentially be used to identify such anomalies on a network level.

For anomaly detection, an “accident mode” defined by the telematics company as an extraordinary large acceleration was used. The “accident mode” allows for the accumulation and storage of accident data (primarily comprising of the three acceleration directions at a data sampling rate of 100 Hz) over a 7 second interval. An “accident” is generally triggered when a certain acceleration (z-direction) threshold is reached. There is not enough memory capacity presently available to store anomaly data at a higher and more sensitive frequency but it forms part of the longer term research study. A potential strategy is to trigger road anomalies which reach a certain “g” threshold (i.e. and does not display the typical behaviour of an accident) and confirm the data reliability via means of road users, or vehicle tracking teams. This anomaly data can then automatically be sent through to road maintenance companies who are responsible for maintenance and or rehabilitation assignments.

An example of anomaly detection by utilising the telematics device’s accelerometer is shown in Figure 7. A vehicle was driven over a road section at a constant speed where a severely distressed area exists (an area where there is a combination of defects such as poor patches, and potholes present). The acceleration values in the x, y and z-direction were plotted on the same set of axes to indicate the response data that the telematics device logged.

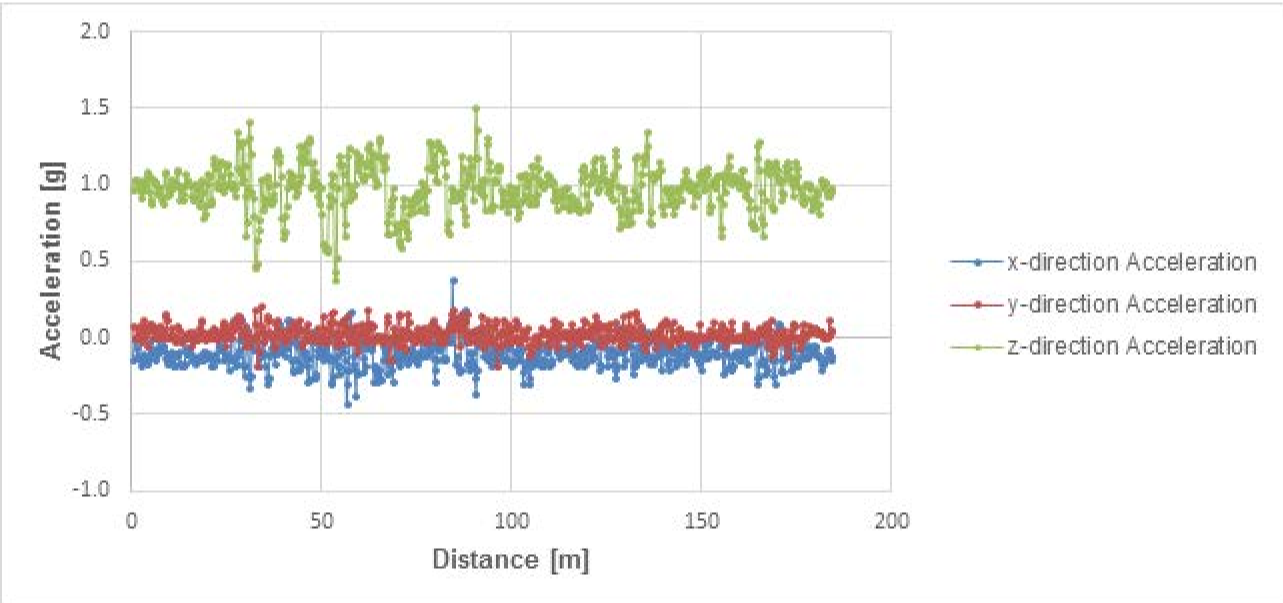

Figure 7 Example of anomaly detection by utilising the telematics device’s accelerometer (“Accident buffer triggering”).

The actual road profile was measured using Class 1 profilometers to validate the high acceleration peaks picked up in the z-direction from the telematics device. The actual road roughness of the section of road can be observed in Figure 8. By comparing the acceleration in the z-direction in Figure 7 with the IRI in Figure 8, it should be noted that more or less similar peaks are generated between approximately the same distance intervals. A spike in the x-direction should be noticed in Figure 7 between distance 50 m and 100 m. This could have occurred due to the vehicle swerving out for a pothole.

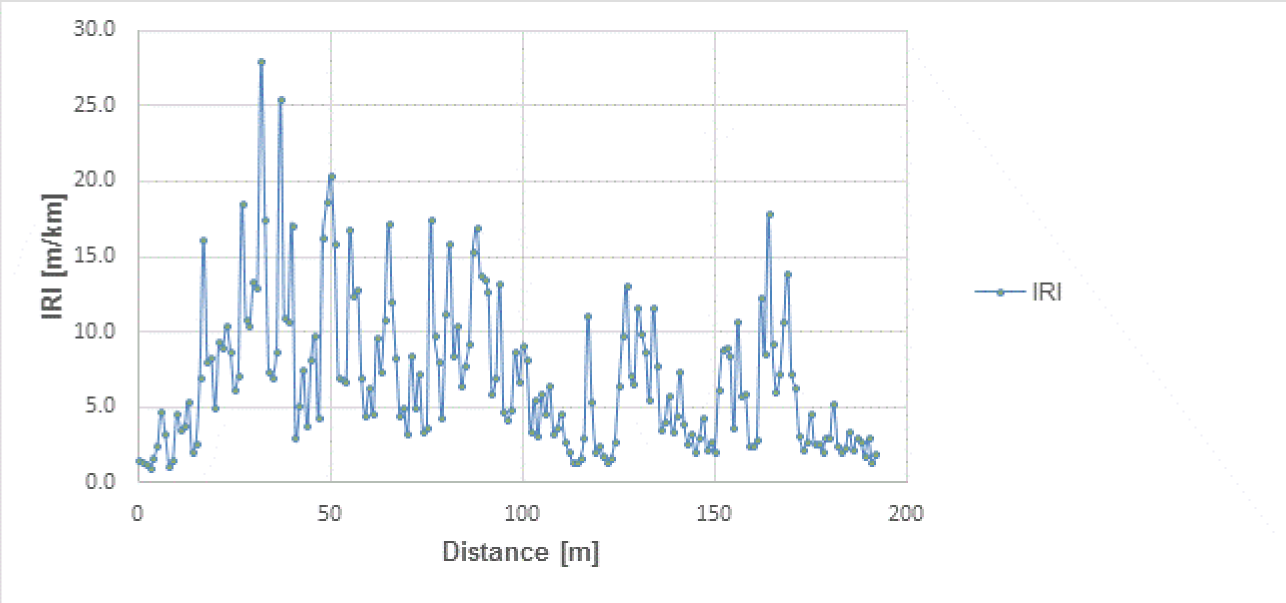

Figure 8 Actual road roughness (IRI) of the road section (SRT, 2014)

More simulations will still be performed to determine applicable "g" thresholds for when a vehicle is travelling over a road anomaly/defect or when a vehicle is in an accident. Numerous opportunities still exist for improvement and this study opens a wide range of new prospects. It can be a beneficial solution to several companies and can significantly assist in improving the road infrastructure.

4. FUTURE DEVELOPMENTS

Technological advancement of any electronic device which continues to deliver accuracy, reliability and consistency requires in-depth investigation, tests and improvements. Several improvements still need to be employed and includes:

- Continue to calibrate the telematics device data against standard IRI data for road sections by incorporating the data for Class 1 profiling devices. This comprises of calibrating the devices for road sections which have different riding qualities (i.e. road sections which is known to have a poor, fair or good riding quality);
- Determine the sample size of vehicles that would be adequate to minimise errors/variability in the data attained;
- Develop unique signatures for different road anomalies/objects. This will be done by evaluating the typical behaviour associated with different road anomalies and by combining the orthogonal acceleration from the accelerometer with the orthogonal rotational acceleration obtained from the gyroscope (e.g. to clarify whether or not a vehicle is travelling over a speed-bump or through a pothole). The main purpose is to develop an algorithm which can process the data and be sent through to companies which adopt GPS technology for road maintenance or rehabilitation assignments or for warning road users beforehand of any possible defects which could be present on the road;

- Monitoring of the riding quality of a road as it deteriorates over time, or is improved due to road maintenance, and
- Develop a method of estimating the roughness of unpaved roads. It is difficult to monitor or measure the condition of unpaved roads with Class 1 profilometer methods, thus investigate the use of utilising telematics technology to determine when unpaved roads should be graded to improve the condition of the road. It is essential to improve the condition of unpaved roads especially when it is used to transport sensitive goods from the farm to the factory. This contributes towards minimising damage or loss of transported goods.

5. CONCLUSION

The objective of this paper is to demonstrate that telematics technology can be an alternative method to measure road condition through a RTRRMS approach. This was illustrated by evaluating data collected from a few typical local passenger vehicles on a standard road section and by utilising the "accident mode" buffer technology currently utilised. Telematics-based technology offers a wide range of benefits around managing the road infrastructure more effectively. It is not only a relatively inexpensive method, but also assists with timeous maintenance of roads which has a direct effect on the safety and comfort of road users. The provision of the large volume of data promotes in covering a wider road network in terms of road condition data cost-effectively.

6. ETHICAL ISSUES

This study only involves the use of aggregated data of a sample size of vehicles which travel on specific route. The confidentiality and privacy information of the clients are thus not affected.

7. ACKNOWLEDGEMENTS

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8. DISCLAIMER

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