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ORIGINAL PAPER

Geomatics techniques for evaluation of road pavement rutting

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Abstract
Rutting is one of the severe pavement distresses. It is defined as longitudinal depression under wheel path, caused by repeated traffic load, and it is an indicator of the structural failure as well as having effect on road user's safety and riding quality. The objectives of this study are to use geomatics techniques such as terrestrial laser scanner, precise positioning system (RTK) and cellular phone for rutting measurements in minor roads in northern part of Jordan, in addition to develop rutting and lateral displacement models using different parameters such as annual average daily traffic (AADT), truck percent, lane width, pavement age and pavement thickness. Manual measurement of rutting was used as reference method for verifying the results obtained from laser scanning, RTK and cellular phone. The study showed that the used methods produced accurate and reliable results compared with the manual method based on root-mean-square (RMSE) which was 0.557 cm for the RTK measurements, 0.577 cm for cellular phone measurements and 0.592 cm of the laser scanner system, respectively. On the other hand, the consistency of accuracy of measurements was slightly better for the cellular phone measurements with a mean average error (MAE) of 0.415 cm, while it was 0.422 cm for the RTK system and 0.442 cm for the laser scanner measurements. The finding of this research will support the development of using geomatics techniques for the measurement of pavement rutting which facilitate the processes and give reliable surface measurement in short time.

Keywords Rutting · Geomatics · Cellular phones · RTK · Laser scanning · Modelling

Introduction and literature review

Roads should be maintained in perfect situation, and maintenance should be carried out periodically. Therefore, detecting road distresses plays a significant role in selecting the maintenance treatments and activities. Rutting, which is one of the major road distresses, should be detected and inspected on the road surface (Attoh-Okine and Adarkwa 2013). Rutting is defined by AASHTO as "a longitudinal surface depression in the wheel path" (Bennett 2002). In addition, it is known as a deformation, which appears as depression along wheel paths of roads, so it is considered the most common pavement permanent deformation distress.

Over the past years, researchers have developed many methods to obtain rutting measurements with a high level of accuracy. These methods can be divided into two categories: manual and automated methods. Manual methods for measuring rut depth as suggested by ASTM 1703 Standard (2010) include straightedge method, rod and level method (ASTM E-1364 2005) which can be used to accurately measure the profile of pavement (Perera et al. 2008) and Dipstick profiler which can be considered the most common method in rutting measurements. The traditional methods to measure rut depth show some limitations and disadvantages such as unsafe operations as the operator may encounter danger when monitoring traffic movements on the lane road, requiring more labour energy and consuming a lot of time. As a result, recent studies show a potential capability for increasing accuracy of (3D) three-dimensional rut measurements over (1D) one rut dimension (Li 2012). On the other hand, the image processing

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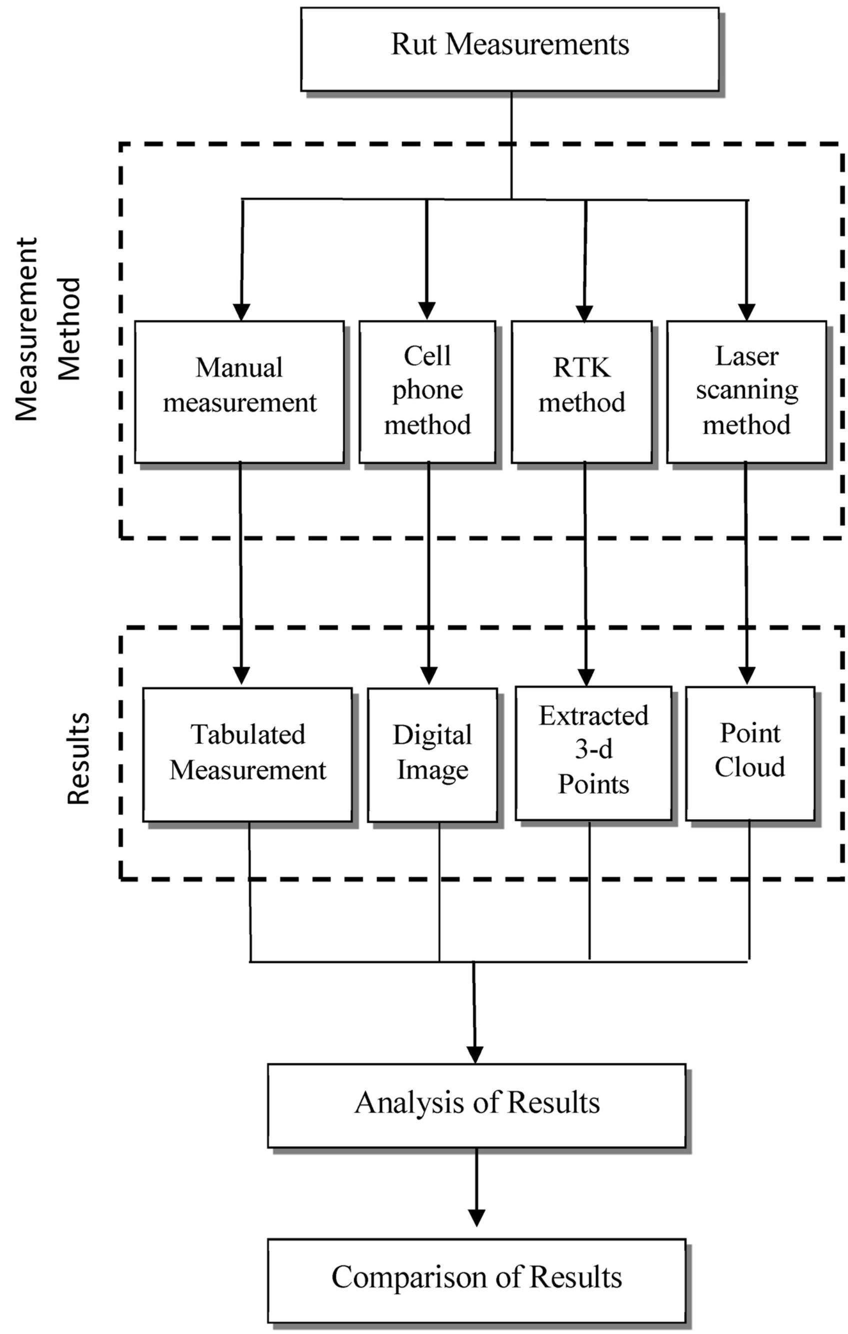

Fig. 1 The used methodology in this research work

techniques for the rut depth purposes are effortless and safe and require less time. In addition, the PC-based stereovision used to measure rut depth has shown outstanding results when it was compared with human operators (Obaidat et al. 1997; and Obaidat 2020). Therefore, the trend in technology is going toward the usage of non-traditional methods such as image processing and smart phones by utilizing advanced technologies as tools for image capturing and analysis of rut depths. In recent years, the world has witnessed an advance in road technology, and this has motivated researchers to develop more technologies and methods to determine rut depth. For example, one of these methods is a point-based rut bar system which uses 3 or 5 laser points to draw a profile of surface of the pavement and calculate the rut depth in traverse direction (Tsai et al. 2015). Shatnawi (2018) used image processing techniques and neural network to detect pavement distresses in secondary roads, based on images acquired by drones. Fuentes et al. (2017) used computer vision techniques to study and detect pavement distresses over several past years and showed how deep learning-based method could affect using different parameters. The automated methods are generally based on a machine or device that is usually installed on a vehicle with a camera or sensors using a sensor bar or the vehicle itself in order to monitor the surface of pavement.

Fig. 2 Setting of grid on road surface

Several systems are using rut bar to determine the length and depth of rutting distress; other systems can determine the width, length and the direction of cracks, as well as the severity and types of cracks (Ahmad et al. 2011). The automated methods are more accurate compared with semi-automated systems. That is basically due to absence of human errors that usually happen when collecting the data using the manual methods. As a result, the computerized methods provide more accurate analysis and, thus, results. Brown and Cross (1992) studied rutting in fourteen states' pavement surfaces in the USA and collected forty-two samples; for each core, the rut results at each site were measured by measuring the rut depth that was extracted from each location. Firoozi Yeganeh et al. (2018) proposed a system to record the rut depth using inexpensive RGB-D (red-green-blue depth) sensors. Thus, the pavement profile has been built from 3D point clouds generated from RGB-D sensors. Marra et al. (2018) introduce a new method to estimate the rutting and compaction on forest soil. The new method works using the photogrammetric system. Aleadelat and Ksaibati (2017) introduce a new method of using smartphones to measure the PSI (present serviceability index) in Wyoming roads. Abdul Qawy et al. (2018) present a system that works to alert the driver on the rutting area before entering it, in order to increase safety and driver vehicle control. Islam (2015) used three axis accelerometer sensors in the smart phones to predict the road roughness as indications of pavement situation. The validations of the system show that the use of smart phones has a good potential in determining the roughness index.

Data collection and methodology

The used methodology of this work consists of three main steps:

1. Selection of measurement method, which includes manual measurements, GPS data collection using real-time kinetic (RTK) method, measurement using cell phone and measurements using laser scanning.
2. Extraction of the results in different formats such as tabulated individual readings from manual measurements, extracted 3D points from GPS readings, digital images from cell phone method and point cloud from laser scanning method.
3. Data analysis and comparison of the results.

Figure 1 shows the used methodology in this research work.

During the data collection stage, setting off road grid with numbering system was located on the surface of road for each section and divided into point due to rut distress location, as shown in Fig. 2. Rut depth was measured by aluminium road and recorded into a table with a reference number for each point.

In order to run laser scanning, several stations were used for each road to cover the whole area. Control points of known coordinates were located on the surface of the road and the shoulder to be used for georeferencing the point clouds. Tie points were also collected and located on the road to be used

Fig. 3 Left: sample of tie points. Right: sample of ground control points

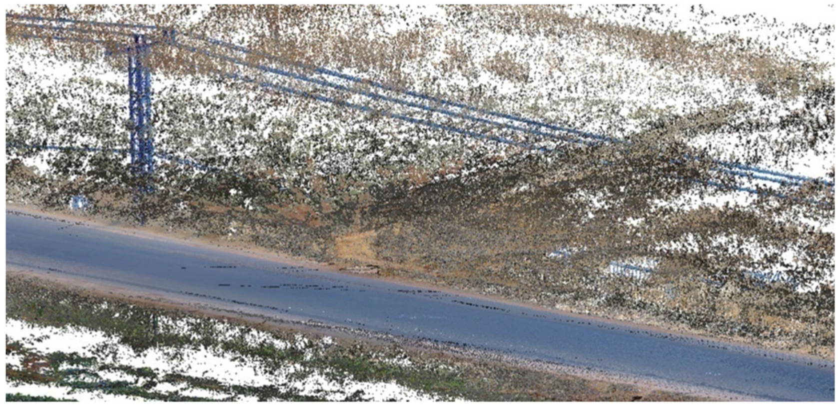

Fig. 4 Registered georeferenced point clouds

for point clouds registration. Figure 3 shows sample of ground control points and tie points. These points are normally used in any geomatics measurements in order to assure accuracy of measurements, rectification, camera calibration and registration of the laser point clouds. In fact, at least three control points have to be used in the rutting measurement's scene.

Fine registration was used in this work using the tie point collected from the field. Scans of each road section were imported as 3D point cloud, and then tie points were identified in the point cloud and linked together in all scenes. This step is necessary for image registration. Using a high number of tie points (fine registrations) along with coarse registration by using natural objects from the field provided high registration accuracy. Result of this step is a georeferenced image from which we can read real 3D measurements for any object in the point cloud. Figure 4 shows a sample of registered georeferenced point cloud. This process is used to match adjacent images in order to fill the gaps of used mapping techniques.

In this research, rutting was also measured using smart phones. Minor road in Irbid governorate with a section length of 200 m was selected due to its low daily traffic and its noticeable rutting. In order to collect data easily from the field, a tool has been fabricated, as shown in Fig. 5 by setting the smart phone on a frame which was connected to a horizontal aluminium rod. This frame is used for practicality of the cellular phone method, scale measurements and portable control plane.

Fig. 5 Image pixel measurements tool for rutting measurements

Rutting depth was measured through cellular phone techniques using the following methodology:

1. A person holds the designed platform with a straight edge above the rutting area.
2. Normal-based camera of optical axe perpendicular to the plane of the platform was used.
3. The images were captured frame by frame in order to compute the rutting depth using a constant scale between ground and image coordinate systems.
4. A control distance of known value was used for scale purpose.

Results and discussion

Three main groups of rutting measurements data were inserted in a sequence arrangement and tabulation: a total of 169 points of rutting measured using the laser scanner method, 221 points of rutting measured using RTK method and manual method and 50 points of rutting measured using cellular phone method and manual method in minor roads in Irbid governorate. Discrepancies of numbers of rutting points among the three different techniques used were due to (1) existence of shadow in some of the images; (2) coverage and computational concepts of the used techniques; (3) variations of levelling between the measured rutting points and the instruments exposure settings; and (4) resolutions, spacing and locations of rutting points. Linear regression analysis for the rutting measurements using laser scanner was conducted after considering different factors and parameters which were extracted, calculated and needed in the analysis. Manual rut measurements (MM) could be predicted as function of the laser

Table 1 Descriptive statistics results between variables for manual and laser scanner methods

Descriptive statistics	Manual measurements (MM)	Laser scanning measurements (LM)	Manual-laser (MM-LM)
N	169	169	169
Mean (cm)	5.520	5.005	0.651
Std. error of mean (cm)	0.177	0.182	0.036
Median (cm)	5.400	4.800	0.550
Mode 1 (cm)	5.000	4.400	0.300
Std. deviation (cm)	2.299	2.236	0.462
Variance (cm)	5.286	5.591	0.214
Skewness	0.613	0.609	0.954
Std. error of skewness (cm)	0.187	0.187	0.188
Minimum (cm)	1.000	0.800	0.000
Maximum (cm)	14.000	12.500	2.000

scanner (LM) as measured independent variable; i.e. MM = *f* (LM).

Descriptive statistics of the road data model was obtained for the inserted variables LM and MM. Table 1 shows the descriptive statistics results and correlation between the variables used in the analysis for the overall road observations.

Manual rutting measurements model for the overall road data observations was formed as shown in Eq. (1):

$$\mathrm{MM} = 0.934 + 0.915\ \mathrm{LM}\ \left(R^2 = 88.6\%, R^2\text{adjusted} = 88.5\%\right) \quad (1)$$

The independent variable had a numerical value as a coefficient used in MM model formation. The LM had a value of 0.915 and the constant had a value of 0.915, which represents the βo value in MM model.

From ANOVA test results, the *p* value for the regression was 0.000, which means that the linear regression equation has good overall significance for predictions with the small values which was zero, with statistical significant model. *F* value from the *F* test was 1299.591 for the regression. In addition, the resulted R-square from the regression analysis was 88.6%, which indicated that the independent variable explained about 96.6% of the variability of the dependent variable MM, with statistical relation. This value showed that the model was perfect with best predictor chosen and followed the linear regression analysis. The R-square value indicated that the MM variable could change by 88.6% from the effect of the independent variable. In addition, the adjusted R-square was 88.5% for the model. Both *p* value and R-square value showed how well the linear regression equation fits the sample data of the roads. The casewise diagnostics with model collinearity diagnostics and residuals were investigated for the model as shown in Tables 2 and 3.

Rutting measurements using laser scanner model figures showed that the normal probability of the model fitted with high degree of certainty and identically on the probability fitted line for the overall road observations with the scattered fitted of standardized residual plot. In addition, the model histogram showed the high frequency distribution of standardized residual with noticeable variety.

The descriptive statistics of the overall road data model were obtained for the inserted variables RM and MM. Several statistical parameters and indicators were obtained from the analysis. The mean of the variables RM and MM was 5.23 and 5.44, respectively. The standard deviation was

Table 2 Collinearity diagnostics summary for laser scanning method

Collinearity diagnostics[a]					
Model	Dimension	Eigenvalue	Condition index	Variance proportions	
				Constant	Laser
1	1	1.905	1.000	0.050	0.050
	2	0.095	4.470	0.950	0.950

[a] Dependent variable: manual

Table 3 Residual statistics summary for laser scanning method

Residuals statistics[a]

	Minimum	Maximum	Mean	Std. deviation	*N*
Predicted value	1.670	12.380	5.520	2.164	169
Residual	−4.528	2.776	0.000	0.776	169
Std. predicted value	−1.779	3.170	0.000	1.000	169
Std. residual	−5.819	3.568	0.000	0.997	169

[a] Dependent variable: manual

calculated for each variable with 2.523 for manual measurements (MM) and 2.48 for RTK (RM). The matrixes were built to describe the relations in an accurate numerical way. Table 4 shows the descriptive statistics results and correlation between the variables used in the analysis for the overall road observations.

Rutting measurement using RTK model for the overall road data observations was formed as in Eq. (2):

$$MM = 0.475 + 0.985\ RM\ \left(R^2 = 96\%, R^2\text{adjusted} = 96\%\right) \quad (2)$$

The independent variable had a numerical value as a coefficient used in MM model formation. The RM had a value of 0.985 and the constant had a value of 0.475, which represents the βo value in MM model.

From the ANOVA table, the *p* value for the regression was 0.000, which means that the linear regression equation has good overall significance for predictions with the small value which was zero, with statistical significance model. *F* value from the *F* test was 5247.329 for the regression. In addition, the resulted R-square from the regression analysis was 96%, which indicated that the independent variable (RM) explained about 96% of the variability of the dependent variable MM, with statistical relation. This value showed that the model was perfect with best predictor chosen and followed the linear regression analysis. The R-square value indicated that the MM variable could change by 96% from the effect of the independent variable. In addition, the adjusted R-square was 96% for the model. Both *p* value and R-square value showed how well the linear regression equation fits the sample data of the roads. The casewise diagnostics with model collinearity diagnostics and residuals were investigated for the model as shown in Tables 5 and 6.

Linear regression analysis for the rutting measurements using cellular phone method was conducted after considering different factors and parameters which were extracted, calculated and needed in the analysis. The analysis was focused on building models for the rut measurements using cellular phone for all roads using the statistical SPSS software. Cellular phone measurements (CM) independent variables were measured, calculated and investigated to get the relation with the dependent variable of manual rut measurements (MM).

$$MM = f\ (CM)$$

Manual measurements (MM) are a function of cellular phone measurements with various statistical descriptions, analysis, relations, graphs and statistics. The independent parameters cellular phone measurement was defined as (CM) with manual measurement (MM) response. Several statistical parameters and indicators were obtained from the analysis. The mean of the variables RM and MM was 6.52 and 6.43, respectively. The standard deviation was calculated for each variable with 1.18 for manual measurements (MM) and 1.35 for cellular measurements (CM). The matrixes were built to describe the relations in an accurate numerical way. Table 7 shows the descriptive statistics results and correlation between

Table 4 Descriptive statistics results for the RTK measurement method

	Manual measurements (MM)	RTK measurements (CM)	Manual-cellular (MM-RM)
N	221	221	221
Mean (cm)	5.440	5.230	0.423
Std. error of mean	0.168	0.170	0.025
Median (cm)	5.300	4.940	0.300
Mode 1 (cm)	4.500	1.180	0.100
Std. deviation (cm)	2.480	2.523	0.365
Variance (cm)	6.154	6.367	0.133
Skewness	0.752	1.022	1.350
Std. error of skewness	0.326	0.164	0.164
Minimum (cm)	0.500	0.710	0.000
Maximum (cm)	14.400	14.830	1.900

Table 5 Collinearity diagnostics and residuals for RTK method

Collinearity diagnostics[a]

Model	Dimension	Eigenvalue	Condition index	Variance proportions	
				Constant	Cellular
1	1	1.901	1.000	0.050	0.050
	2	0.099	4.387	0.950	0.950

[a] Dependent variable: manual

the variables used in the analysis for the overall road observations.

Variable coefficients were determined as results of linear regression analysis to build the rutting measurements using cellular phone model needed for the overall roads. Each variable had a specific coefficient value, with many values resulting for different tests such as *t* test. The analysis of variance results were tabulated in ANOVA table with various values of variable parameters, degree of freedom and *p* value significance of the analysis. R-square of the model was calculated with its adjustment for rutting measurements using cellular phone model of all roads. Rutting measurement using cellular phone model for the overall road data observations was formed as shown in Eq. (3):

$$\mathrm{MM} = 1.653 + 0.757\ \mathrm{CM}\ \left(R^2 = 75.6\%, R^2\text{adjusted} = 75.1\%\right) \tag{3}$$

The independent variable had a numerical value as a coefficient used in MM model formation. The CM had a value of 0.757 and the constant had a value of 1.653, which represents the βo value in MM model.

From the ANOVA table, the *p* value for the regression was 0.000, which means that the linear regression equation has good overall significance for predictions with the small value which was zero, with statistical significant model. *F* value from the *F* test was 148.875 for the regression. In addition, the resulting R-square from the regression analysis was 75.6%, which indicated that the independent variable (CM) explained about 75.6% of the variability of the dependent variable MM, with a statistical relation. This value showed that the model was perfect with best predictor chosen and followed the linear regression analysis. The R-square value indicated that the MM variable could change by 75.6% from the effect of the independent variable. In addition, the adjusted R-square was 75.1% for the model. Both *p* value and R-square value showed how well the linear regression equation fits the sample data of the roads. Casewise diagnostics with model collinearity diagnostics and residuals were investigated for the model as shown in Tables 8 and 9.

Table 6 Residual statistics summary for RTK method

Residuals statistics[a]

	Minimum	Maximum	Mean	Std. deviation	*N*
Predicted value	1.141	14.660	5.471	2.417	220
Residual	− 1.797	1.732	0.000	0.493	220
Std. predicted value	− 1.792	3.802	0.000	1.000	220
Std. residual	− 3.641	3.509	0.000	0.998	220

[a] Dependent variable: manual

Practicality of the used techniques

It is worth mentioning here that the comparison between the three used techniques based on accuracy of measured rutting is not sufficient enough based on technology only. However, other factors such as economical values, operational techniques and requirements for human resources could make added values for the best used technology performance for rutting measurements.

For example, the used laser scanner that is operated by one person could map 300 m × 300 m area during 8 min. Using a mesh of 4 cm × 4 cm, this would produce 2250 rutting points, i.e. equivalent to 281 rutting points/min. This indicates that the laser scanner could produce a bulk and fast rutting measurements if it is used by well-trained human resources.

However, the RTK usage that is operated by 2 to 3 people takes 10 s for every individual rutting measurement, i.e. for every 5 m longitudinal rutting point measurement. This means for every 1 km along the road, it requires to have 200 points that will require 33 min; i.e. each point rutting measurement requires 10 s.

Regarding the usage of cellular phone, two people could carry the measurement task, i.e. one person for camera usage and the other for the setup of the platform (image pixel measurement as shown in Fig. 5). Using this technique, one rutting point could be measured at a time using every mapped image that takes about 2 min. This means 1 km rutting depth

Table 7 Descriptive statistics results and correlation between variables for the cellular phone method

	Manual measurements (MM)	Cellular phone measurements (CM)	Manual-cellular (MM-CM)
N	50	50	50
Mean (cm)	6.52	6.43	0.368
Std. error of mean	0.167	0.191	0.079
Median (cm)	6.550	6.420	0.200
Mode 1 (cm)	4.400	6.530	0.100
Std. deviation	1.180	1.350	0.559
Variance	1.395	1.840	0.313
Skewness	0.107	1.408	4.192
Std. error of skewness	0.662	0.337	0.337
Minimum (cm)	4.400	4.190	0.000
Maximum (cm)	9.300	12.130	3.600

measurements along the road that consists of 200 points will take about 6.7 h, i.e. 2 min/rutting point.

From economical point of view and since time means money, it is clear that laser scanner is the most efficient and practical technique that could be used for rut depth measurement. In fact, it could measure the rut depth within 0.2 s per point; however, the RTK measures that within 10 s and the cellular phone within 120 s.

Conclusions and recommendations

The following conclusions were drawn from this research work:

1. New technology such as laser scanner, RTK and cellular phone could be used efficiently in rut measurements.
2. Laser scanner was the best technology for rutting measurements which could measure rutting in wide range and short time.
3. Rutting measurement models were developed using laser scanner, RTK measurements and cellular phone form the overall road data observations, which appeared reliable according to the statistical analysis results.
4. The study indicated that cellular phones are fast and reliable devices for rut measurements in the field.

Some recommendations are presented in this section based on the data analysis and project experience. Further research and field experience can be effectively directed by these recommendations.

1. It is recommended to use these new technologies for rut depth measurements due to its high accuracy measurements, wide coverage and short time of measuring.
2. Open the door for other civil engineering application in using geomatics techniques.
3. Extracted point clouds from laser scanner can be used and linked with new asphalt finisher for maintenance purpose.
4. RTK and laser scanner are highly recommended to be used in rutting measurements which are considered quite cheap, highly accurate and reliable methods of measurements.

Table 8 Collinearity diagnostics and residuals for cellular phone method

Collinearity diagnostics[a]

Model	Dimension	Eigenvalue	Condition index	Variance proportions	
				Constant	Cellular
1	1	1.979	1.000	0.010	0.010
	2	0.021	9.681	0.990	0.990

[a] Dependent variable: manual

Table 9 Residual statistics summary for cellular phone method

Residuals statistics[a]

	Minimum	Maximum	Mean	Std. deviation	*N*
Predicted value	4.822	10.836	6.522	1.027	50
Residual	−2.336	1.412	0.000	0.583	50
Std. predicted value	−1.656	4.201	0.000	1.000	50
Std. residual	−3.965	2.398	0.000	0.990	50

[a] Dependent variable: manual

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