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Geometric texture indicators for safety on AC pavements with 1 mm 3D laser texture data

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Abstract

Surface texture and friction are two primary characteristics for pavement safety evaluation. Understanding their relationship is critical to reduce potential traffic crashes especially at wet conditions. Texture data obtained from existing systems are restricted on either a small portion on pavement surface or one line-of-sight profile, and the currently used texture indicators, such as Mean Profile Depth (*MPD*), and Mean Texture Depth (*MTD*) only reveal partial aspects of texture property. With the emerging 3D laser imaging technology, acquiring full-lane 3D pavement surface data at sub-millimeter resolution and at highway speeds has been made possible via the newly developed PaveVision3D Ultra data collection system. In this study using 1 mm 3D data collected from PaveVision3D Ultra, four types of texture indicators (amplitude, spacing, hybrid, and functional parameters) are calculated to represent various texture properties for pavement friction estimation. The relationships among those texture indicators and pavement friction are examined. *MPD* and *Skewness* – two height texture parameters, Texture Aspect Ratio (*TAR*) – a spatial parameter, and Surface Bearing Index (*SBI*) – a functional parameter are found to be the four most contributing parameters for pavement friction prediction. Finally a multivariate regression model is developed based on residual plot analysis methods to estimate pavement friction with the *R*-squared value of 0.95. This study would be beneficial in the continuous measurement and evaluation of pavement safety for project- and network-level pavement surveys.

Keywords: 3D texture data; Texture indicators; Pavement friction; Multivariate regression analysis

1. Introduction

Pavement surface texture is defined as the deviation of the pavement surface from a true planar surface or an ideal shape [1]. These deviations occur at several distinct levels of scale, each defined by wavelength (λ) and peak to peak amplitude (A) of its components. Per the texture definition from Permanent International Association of Road Congresses (PIARC), pavement surface texture can be divided into four categories [2,3]: (1) micro-texture ($\lambda < 0.5$ mm, $A \in$ [1–500 μm]); (2) macro-texture ($\lambda \in$ [0.5–50 mm], $A \in$ [0.1–20 mm]); (3) mega-texture ($\lambda \in$ [50–500 mm], $A \in$ [0.1–50 mm]); (4) roughness or unevenness ($\lambda > 500$ mm).

It is widely recognized that pavement surface texture affects many different pavement–tire interactions [4,5]. Wet pavement friction, interior and exterior noise, splash and spray are mainly dependent on macro-texture properties. Dry pavement friction and tire wear are highly associated with micro-texture characteristics. Other tire-pavement interactions e.g. rolling resistance and ride quality are affected by the mega-texture and roughness. Therefore the study on macro-texture property places a vital role in evaluating pavement safety performance. In this study

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texture indicator is defined as an index or parameter to represent attributes of pavement surface texture.

Currently several texture indicators have been used to characterize pavement surface texture. Mean Profile Depth (*MPD*) is the one of the commonly used texture indicator measured using the Circular Track Meter [6] or other laser based measuring systems [7]. The other standardized index is Mean Texture Depth (*MTD*), which is either measured using Sand Patch Method [8] or transformed via *MPD* [7]. Root Mean Square (*RMS*) is measured by several data collection systems, and it can be used as an indicator to represent the amplitude distribution of profile elevations [9,10]. In addition, some other texture indicators such as Hessian Model [11], Power Spectral Density (*PSD*) [12], and Fractal Dimension (*FD*) [13] are also explored to characterize pavement surface texture. However, these parameters only disclose partial aspects of surface texture properties, e.g. *MPD* only reflects the height property of pavement surface.

Pavement friction is a measure of the force generated when a tire slides on a pavement surface, and is dependent on a large number of factors including road types, tire properties, vehicle suspension system, traveling speed, ambient temperature, and the presence of contaminants such as oil and water [3]. Skid resistance is the contribution of roadway surface texture to form or develop this friction, and its value relies on the interaction between pavement surface and vehicle tires. The measurement of skid resistance is critical for monitoring pavement safety performance and preventing accidents on wet roadways. However, frictional measurement devices are relatively complex and costly. During data collection, in most cases a truck carrying a large water tank is needed to wet pavement surface with a prescribed layer of water during measurements, which are unsuitable for network level pavement friction measurement, so the estimation of skid resistance is becoming increasingly important [14–18].

Over the years, many studies have been performed to investigate the relationships between texture indicators and frictional indices, some of which attempt to establish acceptable mathematical models to correlate skid resistance with texture characteristics [19–28]. However, there are several limitations on the use of the existing models to predict pavement friction with texture data in the project- or network-level pavement safety surveys due to the two factors: (1) models are developed in laboratories with good correlations using high resolution data that are normally difficult to acquire in the field; (2) models are developed in fields with low correlations using one line-of-sight profile data, primarily in terms of *MPD*. Therefore there is a need to develop a reliable model for network level pavement friction survey based on texture data with broader pavement surface coverage using a wide range of texture indicators.

In this paper pavement friction prediction model is developed based on the investigation of several texture indicators that are widely used in pavement engineering but also in other fields. To achieve the objective, the 1 mm 3D texture data with full lane coverage are collected using Digital Highway Data Vehicle (DHDV) equipped with PaveVision3D Ultra. Subsequently a series of texture indicators are presented to characterize surface texture properties, including amplitude parameters, spacing parameters, hybrid parameters, and functional parameters. To avoid the use of two texture indicators revealing the similar texture property, the relationships among geometric texture indicators are examined. Finally the comparisons between the predicted and measured friction number are made, and results indicate a good agreement exists between the predicted and measured frictions. The developed approach may be used as a cost-effective and promising method for the network level pavement safety survey.

2. DHDV with PaveVision3D Ultra

DHDV, developed by the WayLink Systems Corporation with collaborations from the University of Arkansas and the Oklahoma State University, has been evolved into the sophisticated system to conduct full lane data collection on roadways at highway speed up to 100 km/h. With the latest PaveVision3D Ultra (3D Ultra for short), the collected texture data has the resolutions of 0.3 mm in vertical direction and 1mm in the longitudinal direction. Fig. 1(a) shows the exterior appearance of the DHDV equipped with the 3D Ultra technology. 3D Ultra is the latest imaging sensor technology that is able to acquire both 2D and 3D laser imaging data from pavement surface through two separate left and right sensors. With the high power line laser projection system and custom optic filters, DHDV can work at highway speed during daytime and nighttime and maintain image quality and consistency. The camera and laser working principle is shown in Fig. 1(b). By illuminating pavement surface using a line laser and acquiring 2D and 3D images using the 3D cameras, the surface intensity variation and range variation in the vertical direction are captured based on the laser imaging triangulation principle, through which the distance from the camera to the pavement is determined for each point on pavement surface (such as P1 and P2).

The 1 mm 3D texture data from 3D Ultra has versatile applications in pavement engineering, such as cracking recognition, rutting measurement, longitudinal and transverse profiling, roughness analysis, faulting measurement, safety analysis, virtual pavement surface reconstruction, and many others. In this study the application of surface texture on pavement friction estimation is explored based on the calculated surface texture indicators.

3. Geometric texture indicators

3.1. Texture characterization techniques

In the past decades several surface characterization techniques have been proposed for various application, and are

(a) (b)

Fig. 1. (a) DHDV exterior appearance; (b) Pavevision3D working principle.

generally grouped into two categories: scale-dependent and scale-independent, as shown in Fig. 2 [29,30].

The scale-independent parameters indicate texture characterization results are independent of the measurement scales (data resolution). Fractal analysis based indicator falls into this category. The scale-dependent parameters mean texture characterization results are dependent on the measurement scales. In other words, the analysis results might be quite different when different measurement scales are used. The scale-dependent parameters can be grouped into five categories: amplitude parameters, functional parameters, spectral analysis, spacing (or spatial) parameters, and hybrid parameters [29].

In this study the four scale-dependent parameters (amplitude, spacing, hybrid, and functional parameters), also termed as geometric texture indicators, are used as the dependent variables to estimate pavement friction. To avoid the use of the two highly correlated texture indicators, the relationships among these texture indicators are investigated as well. Finally pavement safety property in terms of pavement friction is evaluated through a mathematical model developed from the geometric texture indicators.

3.2. Amplitude or height parameters

Amplitude parameter only considers the height or elevation information of surface texture, while ignores the impacts of data spacing on texture properties. For amplitude-related parameters, five texture indicators namely *MPD*, *MTD*, *RMS*, *Skewness*, and *Kurtosis* are presented [29,30].

3.2.1. Mean Profile Depth (MPD)

MPD is a widely accepted and used texture indicator. It is defined as the average of all mean segment depths of all segments of the profile. According to the *MPD* computation practice [2,7], the calculation of *MPD* can be described as follows: the measured profile is divided into different segments which have a length of 100 ± 2 mm, then the segment is divided in two equal halves and the height of the highest peak in each half segment is determined. The

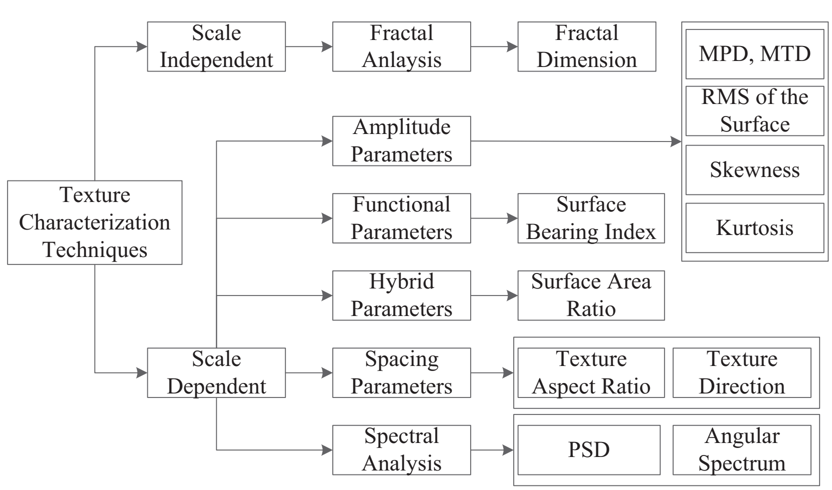


Fig. 2. Schematic diagram of pavement surface characterization techniques.

average of these two peak heights minus the average of all heights is the mean segment depth. The average value of the mean segment depths for all segments making up the measured profile is reported as the *MPD*, as illustrated in Fig. 3.

3.2.2. Simulated Mean Texture Depth (SMTD)

MTD can be viewed as a representation of 3D surface characteristics because it is obtained using volumetric measuring technique [8]. The measured result can be reported as the ground truth. Generally *MTD* can be either measured in field or transformed from *MPD* [7,8]. However, in this study the *MTD* would be calculated with image processing techniques in the 3D domain [31].

A 3D digital image is composed of many discrete height data which are stored in computers as 2D matrix. Assume the sampled pavement surface data can be divided into several areas; each area has a size of N x M mm, and the *SMTD* can be computed using Eq. (1):

$$SMTD = \frac{\int\int_0^D [F_0 - F(x,y)]dxdy}{D} = \frac{\sum_{x=1}^{N}\sum_{y=1}^{M}[F_0 - F(x,y)]}{D} \tag{1}$$

where: $F(x,y)$ – the eight information at point (x,y), D – the integral area which equals to the $M \times N$ pixels, F_0 – the height value being equivalent to the maximum peak in each area D ($M \times N$ pixels)

3.2.3. Root Mean Square (RMS)

RMS is a general measurement of surface texture deviation property. If a larger *RMS* is measured on pavement surface, it indicates there is a significant deviations in surface texture characteristics [29]. This parameter can help interpret contact areas between vehicle tires and pavement surface, and thus is highly associated with surface bearing capacity. Its calculation can be mathematically described with Eq. (2):

$$S_q = \sqrt{\int\int_0^D [z(x,y)]dxdy} = \sqrt{\frac{\sum_{x=1}^{N}\sum_{y=1}^{M} z(x,y)^2}{M \times N}} \tag{2}$$

where: M – the number of points per profile, N – the number of profiles, $z(x,y)$ – the elevation difference between point (x,y) and the mean plane, S_q – the root mean square of the surface.

3.2.4. Skewness (Ssk) and Kurtosis (Sku)

Skewness and *Kurtosis* are used to represent 3D surface texture height distribution properties. Figuratively, a histogram of the heights of all measured points is computed. The symmetry and deviation from an ideal Normal Distribution is represented by *Ssk* and *Sku*, and their mathematical descriptions are given as Eqs. ((3) and (4) [29]:

$$Ssk = \frac{\int\int_0^D [z(x,y)^3]dxdy}{S_q^3} = \frac{\sum_{x=1}^{N}\sum_{y=1}^{M} z(x,y)^3}{M \times N \times S_q^3} \tag{3}$$

$$Sku = \frac{\int\int_0^D [z(x,y)^4]dxdy}{S_q^4} = \frac{\sum_{x=1}^{N}\sum_{y=1}^{M} z(x,y)^4}{M \times N \times S_q^4} \tag{4}$$

where: M – the number of points per profile,N – the number of profiles, $z(x,y)$ – the elevation difference between point (x,y) and the mean plane, S_q – root mean square of the surface.*Ssk* represents the degree of symmetry surface heights about the mean plane. The sign of *Ssk* indicates the predominance of peaks ($Ssk > 0$) or valley structures ($Ssk < 0$) comprising the surface. *Sku* indicates the presence of the inordinately high peaks/deep valleys ($Sku > 3.00$) making up the texture. If surface heights are normally distributed, then *Ssk* is 0.00 and *Sku* is 3.00. Similarly, surface heights are positively skewed ($Ssk > 0$) or negatively skewed ($Ssk < 0$). Surface height distributions can be considered as the slow variation ($Sku < 3$) or extreme peaks or valleys ($Sku > 3$). The less the *Sku* is, the smaller the height variation is. The larger the *Sku* is, the larger the height variation is.

3.3. Spacing or spatial parameters

Texture on pavement surface may have anisotropic or isotropic patterns. Autocorrelation Function (*ACF*) is one of the most effective and robust approach for texture pattern recognition [29]. The *ACF* is determined by taking a duplicate surface $Z((x - \nabla x), (y - \nabla y))$ of the measured surface $Z(x,y)$ with a relative lateral displacement $(\nabla x, \nabla y)$ and mathematically multiplying the two surfaces. Subsequently, the resulting function is integrated and normalized to yield a measure of the degree of overlap between

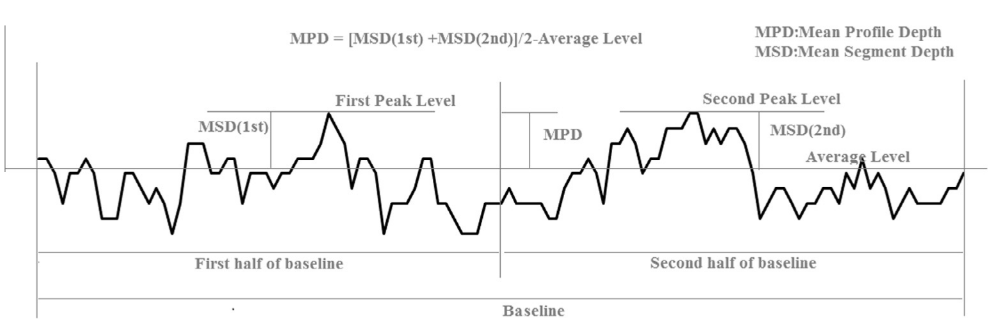


Fig. 3. A general procedure for *MPD* calculation.

the two functions. The *ACF* is a measure of how similar the texture is at a given distance from the original location.

Generally the *ACF* of the anisotropic pavement surface has the fastest decay along the direction perpendicular to the predominant texture direction and the slowest decay along the texture direction, as shown in Fig. 4a. The *ACF* of isotropic pavement surface has the similar texture aspects in all direction, so it is difficult to determine the fastest and slowest decay of the test sample, as shown in Fig. 4b. For isotropic pavement surface, it is impossible to normalize the *ACF* of the fastest and slowest decay to 0.2 that is a threshold to determine the fastest and slowest decay.

Texture Aspect Ratio (*TAR*) is a measure of the spatial isotropy or directionality of the surface texture. The length of fastest decay is a measure of the distance over the surface such that the new location will have minimal correlation with the original location. On the other hand, the length of the slowest decay is a measure of the distance over the surface such that the new location will have maximum correlation with the original location. The *TAR* is computed as the ratio of the length of fastest decay to the length of the slowest decay, as mathematically described in Eq. (5):

$$0 < TAR = \frac{\text{The distance that the normalized ACF has the fastest decay to 0.2 in any possible direction}}{\text{The distance that the normalized ACF has the slowest decay to 0.2 in any possible direction}} \leqslant 1 \tag{5}$$

In principle, the Texture Aspect Ratio has a value between 0 and 1. Larger values, say $TAR > 0.5$, indicate stronger isotropic or uniform texture aspects in all directions, whereas the smaller values, say $TAR < 0.3$, indicate the stronger periodic texture properties.

3.4. Hybrid parameters

Hybrid parameter is used to overcome some weaknesses of amplitude and spatial parameters. Its calculation depends on both the height and spacing information, and thus any changes that occur in either amplitude or spacing may have an effect on the hybrid property [29,30]. This parameter can be computed as: the ratio of the interfacial area of a surface over the sampling area. The areal element can be expressed using the smallest sampling quadrilateral ABCD, as shown in Fig. 5.

Since the four corners of the quadrilateral may not be on the same plane, the interfacial area of the pile-up element may be considered to consist of two triangles, either *ABC* & *ACD* or *ABD* & *BCD*. The interfacial area of the quadrilateral is defined as an average of two sets of triangle areas (*ABC* & *ACD* and *ABD* & *BCD*) and its computation principle is given by Eq. (6):

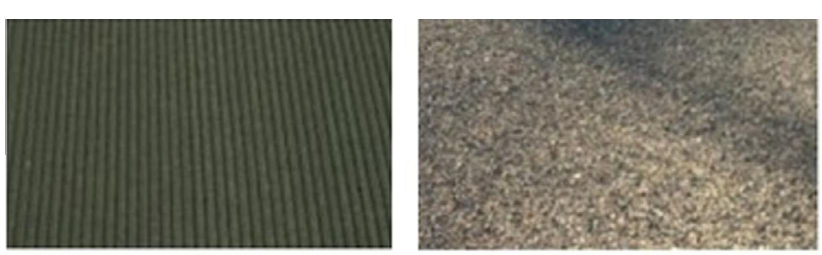
$$\begin{aligned} A_{ij} &= \frac{1}{4}(|\overrightarrow{AB}| + |\overrightarrow{CD}|)(|\overrightarrow{AD}| + |\overrightarrow{BC}|) \\ &= \frac{1}{4}\Big\{([\Delta y^2 + (f(x_i, y_j) - f(x_i, y_{j+1}))^2]^{\frac{1}{2}} \\ &\quad + [\Delta y^2 + (f(x_{i+1}, y_{j+1}) - f(x_{i+1}, y_{j+1}))^2]^{\frac{1}{2}} \\ &\quad + [\Delta x^2 + (f(x_i, y_j) - f(x_{i+1}, y_j))^2]^{\frac{1}{2}} \\ &\quad + [\Delta x^2 + (f(x_i, y_{j+1}) - f(x_{i+1}, y_{j+1}))^2]^{\frac{1}{2}})\Big\} \end{aligned} \tag{6}$$

The total interfacial area on the surface can be computed using Eq. (7):

$$A = \sum_{j=1}^{N-1}\sum_{i=1}^{M-1} A_{ij} \tag{7}$$

Then the calculation of surface areal ratio is given as Eq. (8):

$$SAR = \frac{(A - (M-1)(N-1) \times \Delta x \times \Delta y)}{(M-1)(N-1) \times \Delta x \times \Delta y} \tag{8}$$



(a) (b)

Fig. 4. Photographs of (a) anisotropic pavement surface; (b) isotropic pavement surface.

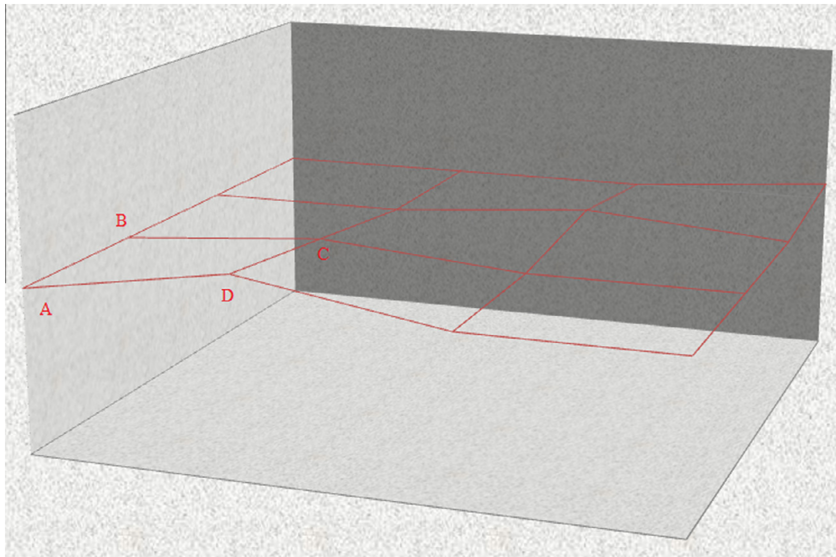


Fig. 5. Schematic diagram of the interfacial area.

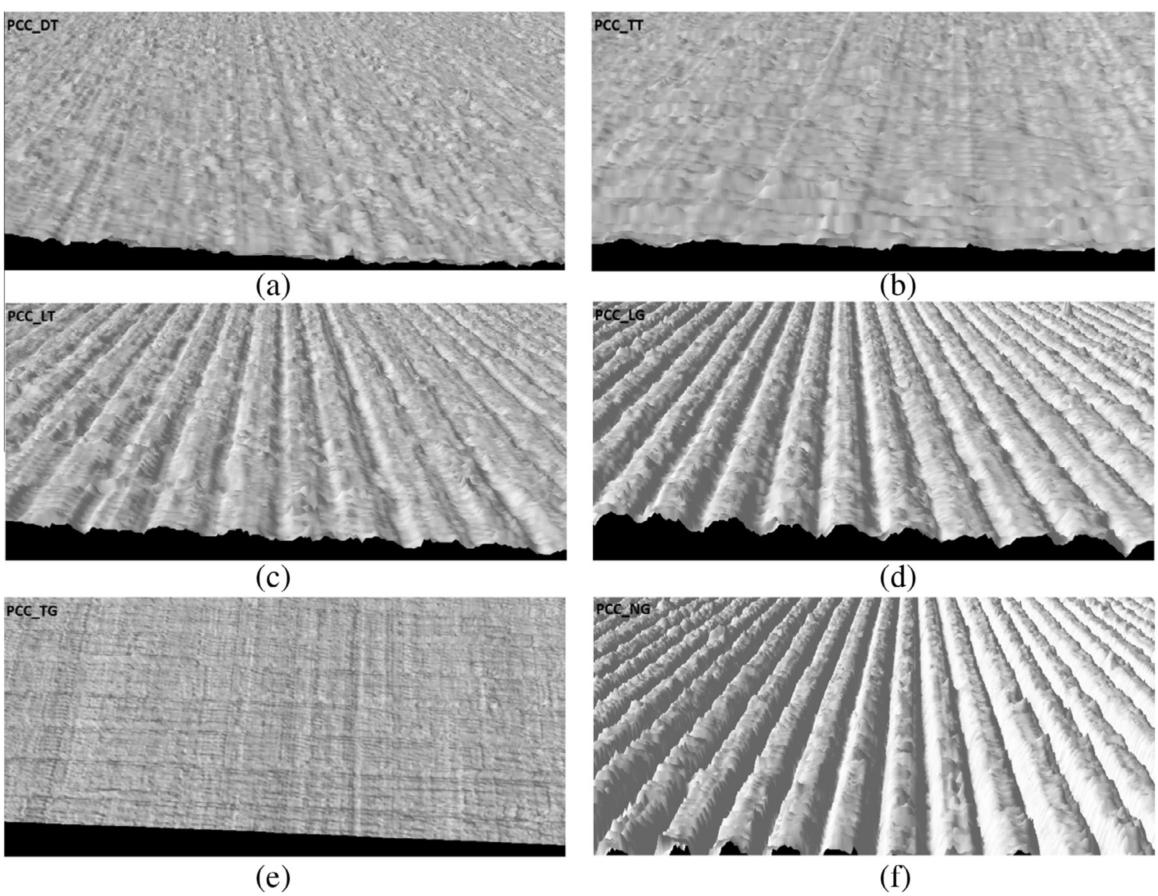


Fig. 6. 3D rendering of test specimens (a) PCC_DT; (b) PCC_TT;(c) PCC_LT; (d) PCC_LG; (e) PCC_TG; (f) PCC_NG.

The developed interfacial area ratio reveals the hybrid property of surfaces. A large value indicates the significance of either the amplitude or the spacing or both.

3.5. Functional parameters

The functional parameters are highly related to their functions i.e. wearing or friction. In this study Surface

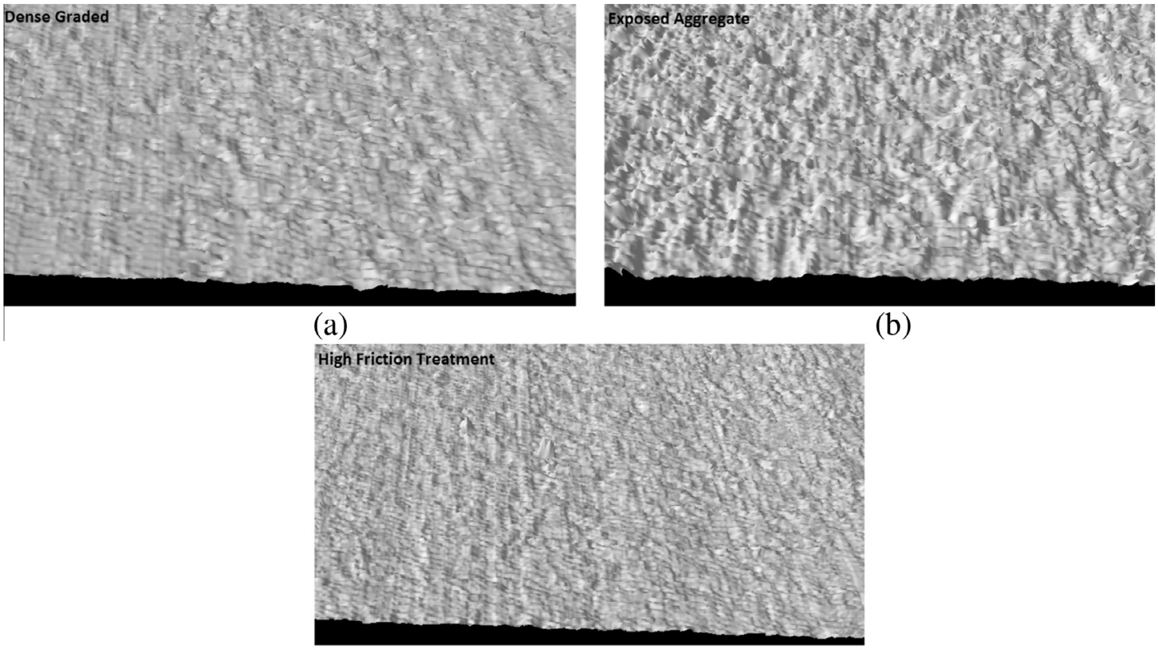


Fig. 7. 3D rendering of test specimens (a) AC_DG; (b) AC_EA;(c) AC_HF.

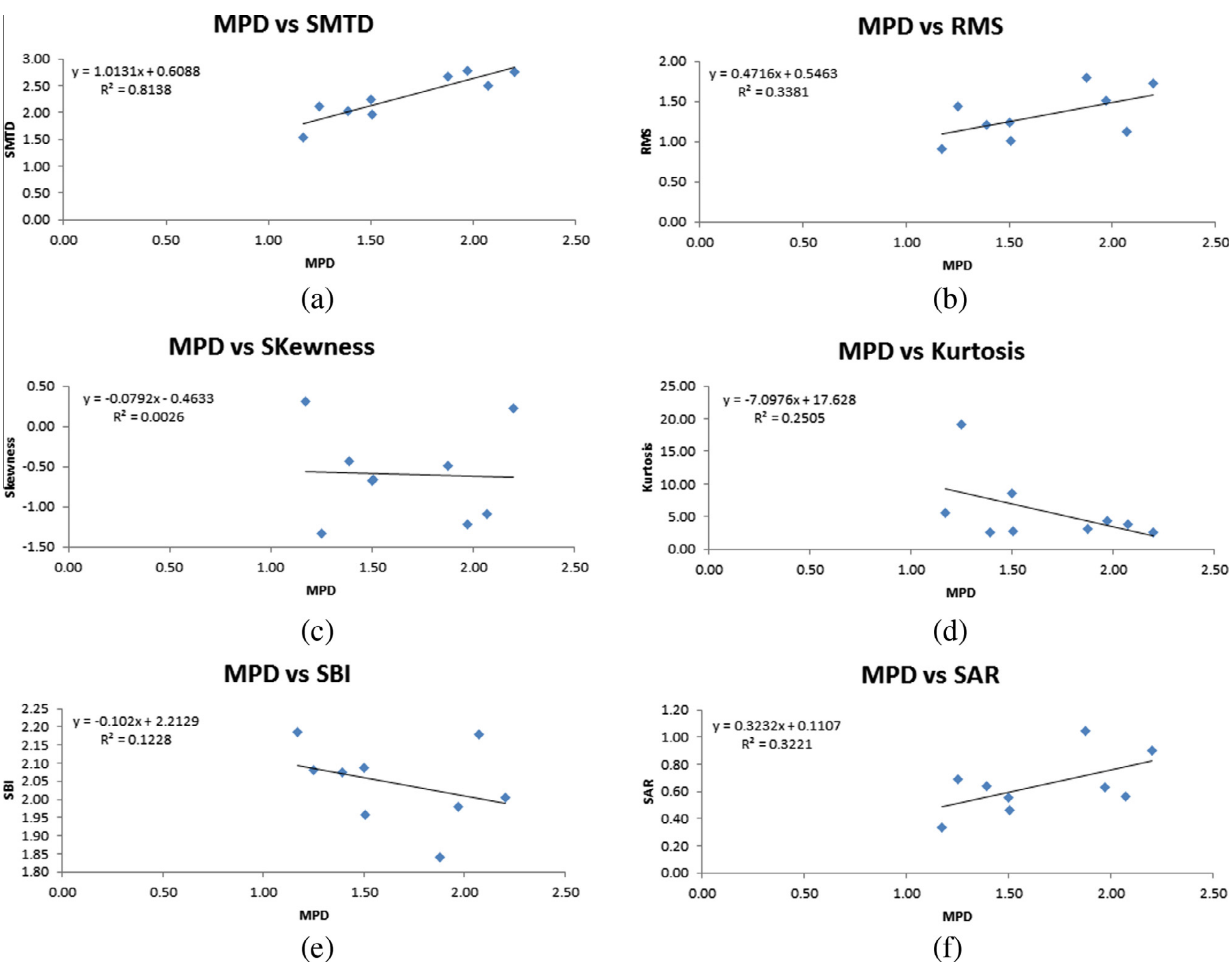


Fig. 8. Correlation results (a) *MPD* vs *SMTD*; (b) *MPD* vs *RMS*; (c) *MPD* vs *Skewness*; (d) *MPD* vs *Kurtosis*; (e) *MPD* vs *SBI*; (f) *MPD* vs SAR.

Bearing Index (*SBI*) was found to have a very close relation with the wearing properties of the surface [29], and equals to the ratio of the root mean square to the surface height at a 5% bearing area, as described using Eq. (9).

$$SBI = \frac{\sqrt{\int\int_0^D [z(x,y)]dxdy}}{H_{5\%}} = S_q/H_{5\%} \tag{9}$$

where S_q – root mean square; $H_{5\%}$ – the surface height at 5% bearing area.

4. Correlations among geometric texture indicators

Relationships among the geometric texture indicators are explored in this study. If the two texture indicators have a high correlation with the R^2 value greater than 0.8, one of them is excluded since they reveal the similar texture properties. However, for two texture indicators having a poor correlation (e.g. $R^2 \leqslant 0.6$), both are considered to include two different texture properties, and thus the two texture indicators are kept in the model development.

Two groups of samples are chosen to examine the relationships among different geometric texture indicators. The first sample group includes six test specimens. Each specimen is constructed with a different texturing technique. Fig. 6a demonstrates the six rigid pavements with turf dragged texture (Fig. 6a), transversely tined texture (Fig. 6b), longitudinally tined texture (Fig. 6c), longitudinally grooved texture (Fig. 6d), transversely grooved texture (Fig. 6e), and Next Generation Concrete Surface (NGCS) (Fig. 6f).

The second sample group contains three test specimens. Each specimen has obvious different texture properties: AC pavement constructed with dense graded surface (Fig. 7a), AC pavements with exposed aggregate surface (Fig. 7b), and high friction treated surface (Fig. 7c).

Correlation analyses are performed among the indicators with the following observations:

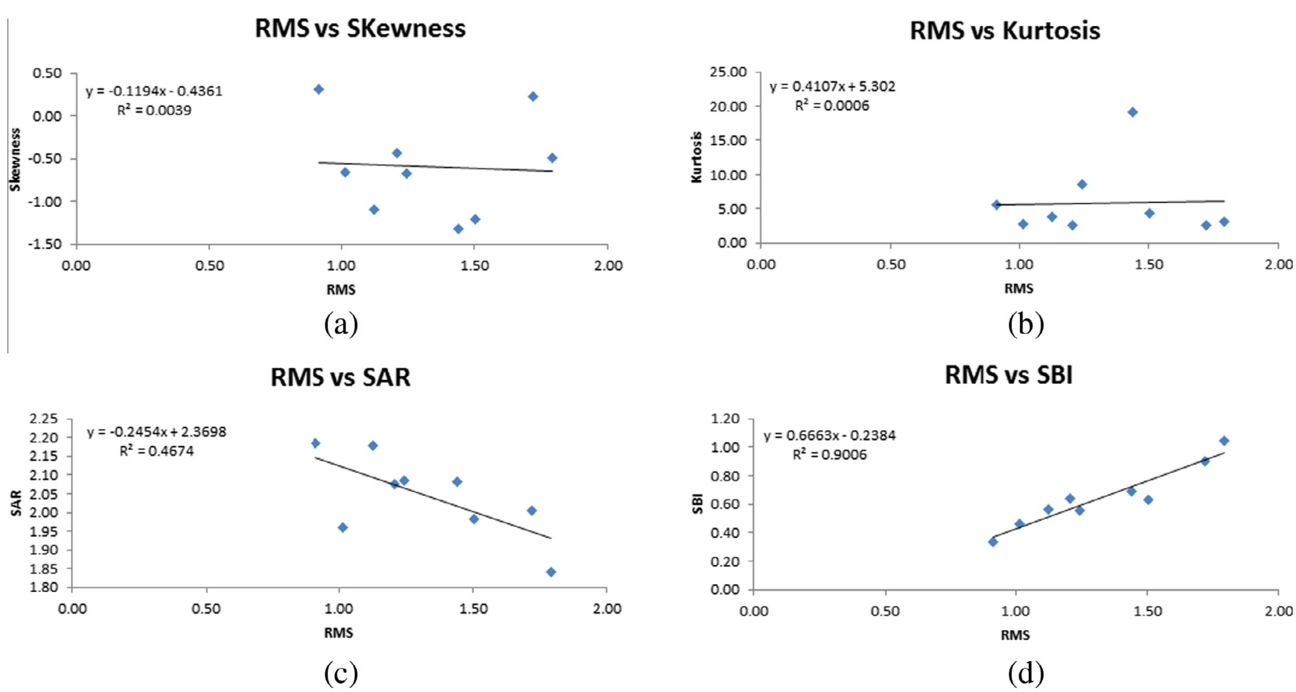


Fig. 9. Correlations results (a) *RMS* vs *Skewness*; (b) *RMS* vs *Kurtosis*; (c) *RMS* vs SAR; (d) *RMS* vs *SBI*.

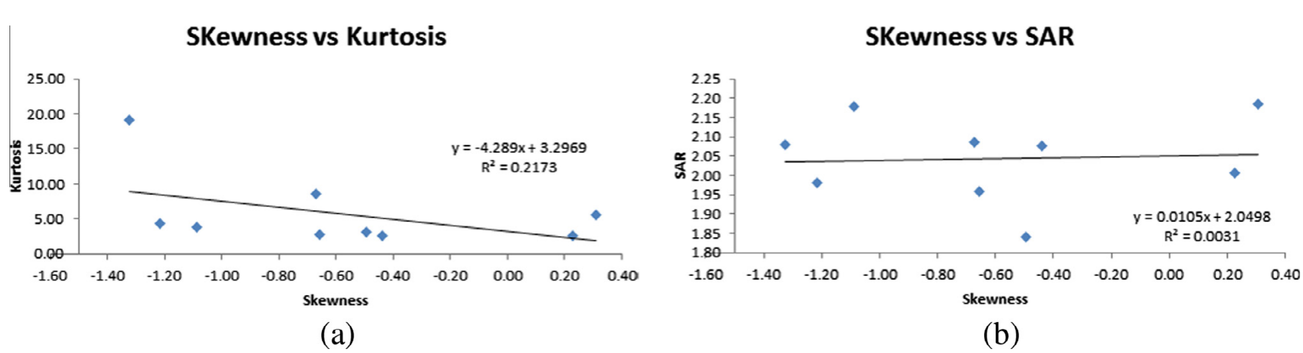


Fig. 10. Correlation results (a) *Skewness* vs *Kurtosis*; (b) *Skewness* vs *SBI*.

- Fig. 8 shows there is no good correlation between *MPD* and other texture indicators with one exception of *SMTD*. In this case *MPD* is applied in model development to describe the amplitude property of surface texture.
- Fig. 9 indicates a good correlation is observed between *RMS* and *SAR*, with an *R*-squared value of 0.9, and thus *SAR* is used to describe the hybrid property of surface texture.
- Fig. 10 indicates no good agreements exist between *Skewness* and *Kurtosis* or *SBI*. Both of them should be kept to disclose surface texture properties.
- Fig. 11 shows there is a poor correlation between *Kurtosis* and *SBI*.

Based on correlation analysis results, *MPD*, *Skewness*, *Kurtosis*, *TAR*, *SAR*, and *SBI* are capable of disclosing different aspects of surface texture properties, and are used for the development of pavement friction prediction model.

5. Pavement friction model development and case study

5.1. Route description

To explore the relationships between the six surface texture indicators and pavement friction, one pavement section is chosen as the test bed in this study. AL-I 65 data collection starts at GPS coordinate of 32.387859, −86.322212, and ends at GPS coordinate of 32.390949, −86.321396, with a total length of approximately 393 m. The data collection site is the ramp from NB I-65 to EB SH152 (Northern Blvd.), as shown in Fig. 12.

The route consists of two surface types: High Friction Surface Treatment (HFST) and the regular AC pavement surface type. HFST is located in the middle of the test section. The regular surface is located at the lead-in and lead-out segments.

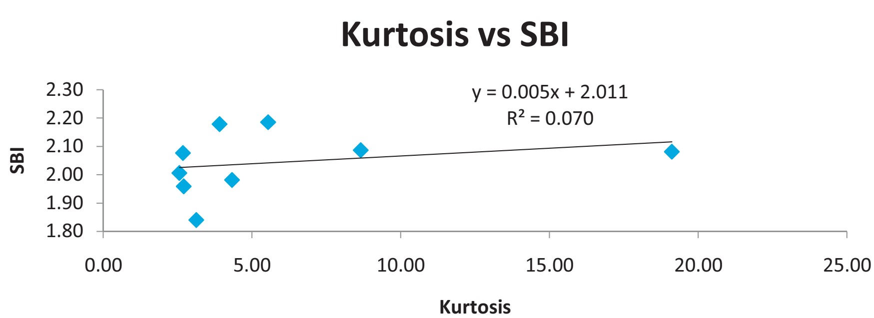


Fig. 11. Correlation result between *Kurtosis* and *SBI*.

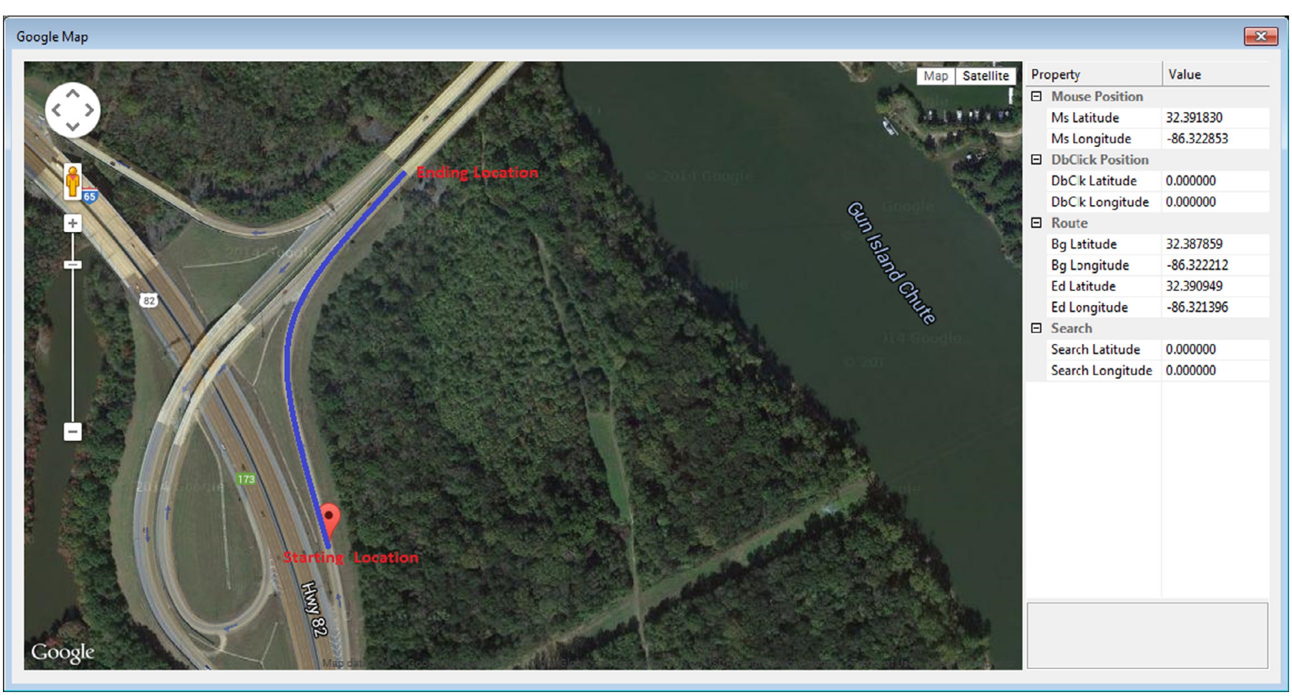


Fig. 12. AL-I 65 field test site.

5.2. Friction field measurement

In this study the friction data are acquired with Dynatest 6875 Highway friction tester, and 1 mm 3D texture data are collected using DHDV with Pavesion3D Ultra. The test section is sampled into 84 segments, and each segment has a length of 4.57 m (two 3D image long). The HFST segment starts from approximately 95 m and ends at approximately 301 m, as marked in Fig. 13.

To validate the reliability of the collected friction data, three repetitive measurements are conducted. Note that the three measurements show consistent results with the correlation coefficients of 0.95, 0.98, and 0.95, respectively. In this study the mean friction numbers (FNs) from the three measurements are used for model development and validation.

5.3. Pavement friction prediction

5.3.1. Model development

As presented in Section 4, six texture indicators, namely *MPD*, *Skewness*, *Kurtosis*, *TAR*, *SAR*, and *SBI* are selected for pavement friction model development. Based on the multivariate regression analysis, pavement friction (FN_p) can be estimated with the six texture indicators, as mathematically described in Eq. (10).

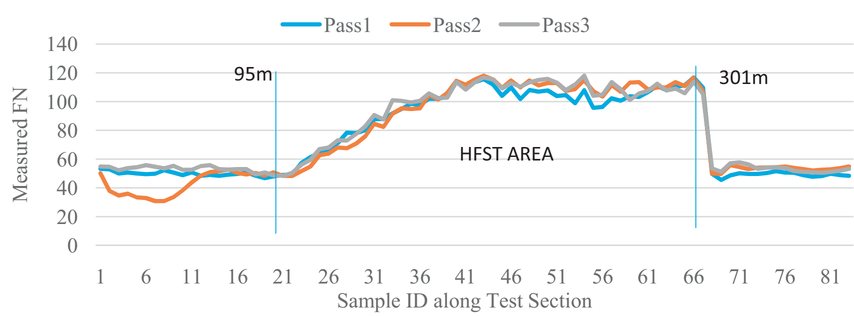


Fig. 13. Friction measurement results on AL I 65 ramp.

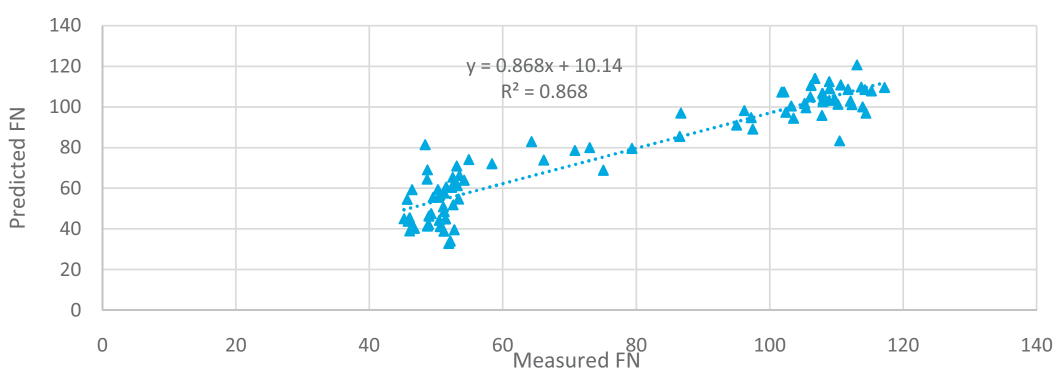


Fig. 14. Correlation results between the predicted and measured FNs.

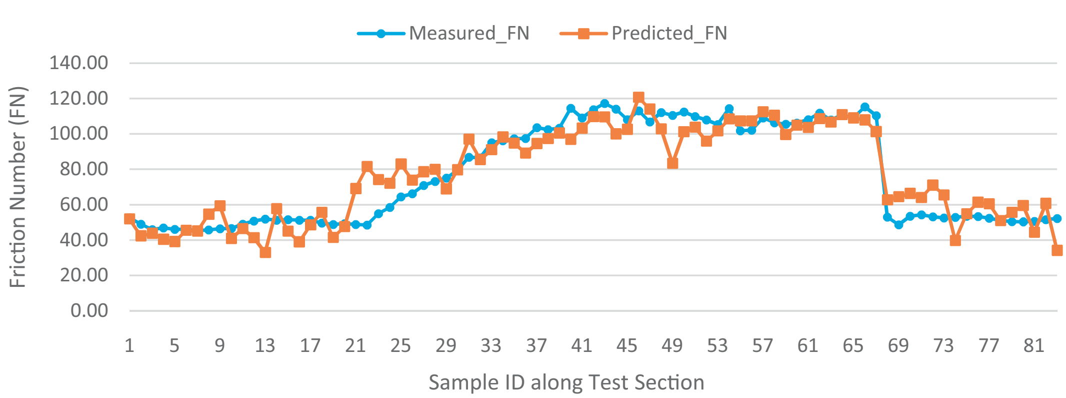


Fig. 15. Comparison of the measured and predicted FNs from six texture indicators.

$$FN_p = 52.41MPD + 6.91Skewness - 1.15Kurtosis + 15.32TAR - 108.92SAR + 63.67SBI - 140.69 \quad (10)$$

Fig. 14 shows the correlation results between the predicted and measured *FNs* based on the multivariate regression analysis, with an *R*-squared value of 0.868. Note that a good agreement appears at the lead-in and HFST segments, but a large difference exists at the lead-out segment, as illustrated in Fig. 15. In addition, the sensitivity analyses of the predicted *FNs* to the six texture indicators indicate that *Kurtosis* and *SAR* have no significant influences on the predicted *FNs* based on the *p*-values (e.g. $p > 0.05$), as shown in Table 1. Accordingly pavement friction enables to be estimated with the four indicators: *MPD*, *Skewness*, *TAR*, and *SBI*.

The multivariate regression analysis indicates the correlation coefficient between the predicted and measured *FNs* is around 0.86 when the four variables are used to estimate pavement friction, and the corresponding model coefficients are given in Table 2. Note that the *p*-value for each variable is less than 0.05, indicating the developed model is statistically significant for pavement friction prediction. The developed model can be mathematically described using Eq. (11).

$$FN_p = 48.27MPD + 7.38Skewness + 12.34TAR + 59.42SBI - 105.58 \quad (11)$$

5.3.2. Model verification and improvement

In this model the effects of each independent variables (e.g. *MPD*) on dependent variables (e.g. *FN*) are assumed to be linear. If the effects of the independent variables on the dependent variables appear to be non-linear, this model may not be the appropriate fit for the data. In this study the residual plots is used to investigate the linear effects of independent variable on the dependent variable. The residual plot shows the residuals (the differences between the measured and predicted values) on the vertical axis and the independent variable on the horizontal axis. If the points in a residual plot are randomly distributed around the horizontal axis, a linear regression model may be appropriate for the data; otherwise, a non-linear model is more appropriate [32]. Fig. 16 shows the residual plots of the four variables.

Note that the Fig. 16b and d show a random dispersion around the horizontal axis, indicating the linear models can be applied on these two variables to predict pavement friction. Fig. 16a and c show non-random patterns (U-shaped or inverted U-shaped) are observed for the *Skewness* and *TAR*, indicating the non-linear models should be used for the two variables. Based on Fig. 17(a), a non-linear model should be developed to fit the FNs with the independent variable "*MPD*". After several trial-and-error, a three-order polynomial model is employed with the largest R-squared value. Similarly, exponential model is developed for the *SBI* to fit the measured FNs as shown in Fig. 17b. Subsequently, data transformation is performed.

In the subsequent multivariate analysis, the original *MPD* and *SBI* are replaced by the transformed *MPD* and *SBI* calculated from the developed models, and the multivariate regression analysis results are given in Table 3. Note that the p-values are approaching to the zero, indicating the newly developed model are statistically more significant for pavement friction prediction. As a result, a new model can be developed with the four variables: *MPD*, *Skewness*, *TAR*, and *SBI*, as mathematically described in Eq. (12).

$$FN_p = -714.15MPD^3 + 2256.43MPD^2 - 2264.432MPD + 7.04Skewness + 13.43TAR + 5.89e^{0.94SBI} + 743.93 \quad (12)$$

Table 1
Multivariate regression results from the six texture indicators.

	Coefficients	Standard error	*t* stat	*p*-Value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	−140.69	29.02	−4.85	0.00	−198.48	−82.90	−198.48	−82.90
MPD	52.42	6.59	7.95	0.00	39.29	65.54	39.29	65.54
Skewness	6.91	1.77	3.90	0.00	3.38	10.45	3.38	10.45
TAR	15.32	5.47	2.80	0.01	4.42	26.23	4.42	26.23
SBI	63.67	5.02	12.69	0.00	53.68	73.67	53.68	73.67
Kurtosis	−1.15	3.50	−0.33	0.74	−8.13	5.82	−8.13	5.82
SAR	108.92	81.24	1.34	0.18	−52.89	270.72	−52.89	270.72

Table 2
Multivariate regression results from *MPD*, *Skewness*, *TAR*, and *SBI*.

	Coefficients	Standard error	*t* stat	*p*-Value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	−105.58	9.79	−10.78	0.00	−125.08	−86.09	−125.08	−86.09
MPD	48.27	5.96	8.09	0.00	36.39	60.14	36.39	60.14
Skewness	7.38	1.31	5.63	0.00	4.77	9.99	4.77	9.99
TAR	12.34	5.06	2.44	0.02	2.27	22.41	2.27	22.41
SBI	59.42	4.10	14.49	0.00	51.26	67.59	51.26	67.59

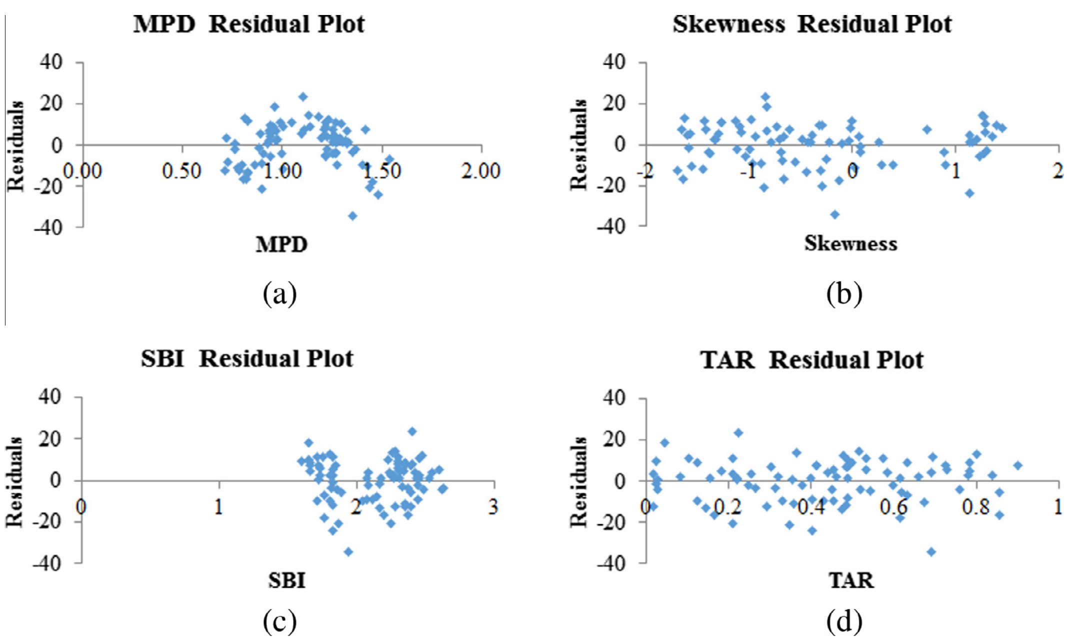


Fig. 16. Residual plots of the four variables: (a) *MPD*; (b) *Skewness*; (c) *SBI*; (d) *TAR*.

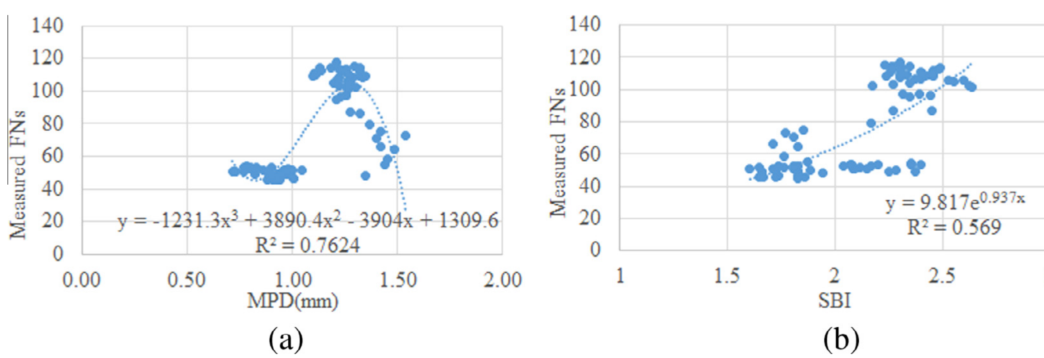


Fig. 17. Non-linear models development for (a) variable *MPD* and (b) variable *SBI*.

Table 3
Multivariate regression results from *Skewness*, *TAR*, NEW_*MPD* and NEW_*SBI*.

	Coefficients	Standard error	*t* stat	*p*-Value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	−15.64	4.68	−3.34	0.00	−24.96	−6.32	−24.96	−6.32
Skewness	7.04	1.18	5.96	0.00	4.69	9.39	4.69	9.39
TAR	13.43	4.43	3.03	0.00	4.61	22.26	4.61	22.26
NEW_*MPD*	0.58	0.06	9.50	0.00	0.46	0.70	0.46	0.70
NEW_*SBI*	0.60	0.07	8.64	0.00	0.46	0.74	0.46	0.74

5.3.3. Correlation between the predicted and measured FNs

The measured *FNs* are correlated with the predicted *FNs* from the Eq. (12), with an *R*-squared value of 0.895. Apparently there are three outliers among the test samples due to their large deviations from the fitting line, as illustrated in Fig. 18a. After the influences of the outliers on the developed models are eliminated, a new linear model can be developed, with an *R*-squared value of 0.947, as shown in Fig. 18b.

As a result, pavement friction can be estimated based on the four texture indicators: *MPD*, *Skewness*, *TAR*, and *SBI*. *MPD* and *Skewness* belong to the amplitude parameters representing surface height distribution. *TAR* belongs to the spacing parameters, describing pavement surface texture pattern. *SBI* belongs to the functional parameters, disclosing surface bearing capacity and pavement frictional properties.

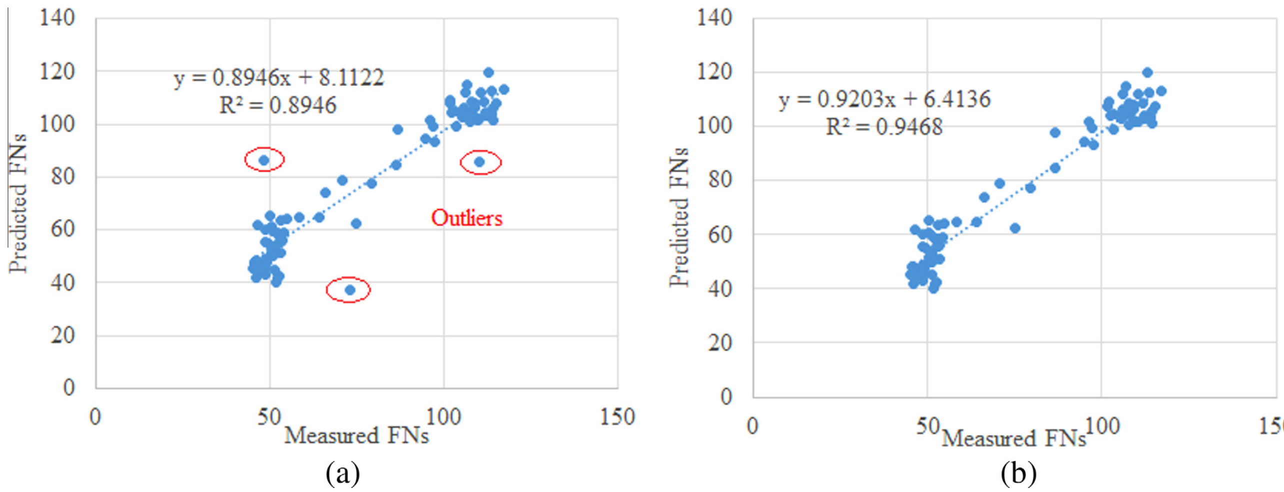


Fig. 18. Correlation results between the predicted and measured FNs (a) with outliers; (b) after outlier removal.

6. Conclusions

This study examines eight surface texture indicators and their application on pavement friction prediction with 1 mm 3D laser texture data. The eight surface texture indicators are grouped into four categories: amplitude parameters (including *MPD*, *SMTD*, *RMS*, *Skewness*, and *Kurtosis*), spacing parameters (*TAR*), hybrid parameters (*SAR*), and functional parameters (*SBI*). To avoid the use of two highly correlated texture indicators, correlation analyses are conducted. It is found that (1) *SMTD* are highly correlated with *MPD*; (2) *RMS* is highly correlated with *SAR*. As a result, six texture indicators are used to characterize surface texture characteristics, namely *MPD*, *Skewness*, *Kurtosis*, *TAR*, *SAR*, and *SBI*. Subsequently, pavement friction prediction model is developed based on multivariate regression analysis. The findings from the presented research can be used to predict pavement friction based on various texture indicators including amplitude (*MPD*, *Skewness*), spacing (*TAR*), and functional (*SBI*) parameters. This study would be beneficial in the continuous measurement and evaluation of pavement safety for the project- and network-level pavement surveys.

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