High-Definition Field Texture Measurements for Predicting Pavement Friction

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ABSTRACT

Monitoring and managing skid resistance properties are crucial activities to reduce the number of highway accidents and fatalities. However, current methodologies to measure pavement surface friction present several disadvantages that make them impractical. Thus, it is necessary to evaluate alternative methods to estimate friction. The principal objective of this study was to develop friction models based on pavement texture. We implemented a Line Laser Scanner (LLS) to obtain an improved characterization of the pavement texture which includes macrotexture and incorporates microtexture description using eight different parameters. Field measurements of friction and texture were collected around Texas using the British Pendulum Test (BPT), the Dynamic Friction Test (DFT), the micro-GripTester, and the LLS. The experimental results showed that there is not a unique relationship between texture and friction, its relation is strong and statistically significant, but it is different for each type of pavement surface. Thus, regression analysis pooling all data cannot be utilized to quantify this relationship. For this reason, we applied a panel data analysis approach that allows the incorporation of the type of surface and provides a more robust analysis. The results indicate that the prediction of friction is significantly improved when incorporating information from both macrotexture and microtexture into the prediction model. Therefore, a measure of microtexture should be included into friction models based on texture. Also, the study of different texture parameters suggests that the mean profile depth (MPD) is the most significant parameter for macrotexture and for microtexture to explain the distinct friction measures.

Keywords: friction, skid resistance, macrotexture, microtexture, laser scanner, data analysis.

INTRODUCTION

Highway surface skid resistance has a significant influence on the number of wet weather accidents. Research conducted by the National Transportation Safety Board (NTSB) and the Federal Highway Administration (FHWA) in 1980 indicates that about 70% of wet pavement crashes can be prevented or minimized by improving pavement friction *(1)*. Therefore, monitoring and managing skid resistance properties is crucial to reduce the number of highway accidents and fatalities. Pavement surfaces should be designed, constructed, and maintained to provide durable and adequate skid resistance properties for drivers. Current methodologies to measure pavement surface friction present several disadvantages that make them impractical for field data collection over large highway networks. For instance, most tests require water application to simulate the wet condition. The use of water limits the continuity of the test over long distances and affects its efficiency. Additionally, some methods require traffic control, which can be costly, time-consuming and present safety concerns. Thus, it is important to study different ways to estimate surface friction characteristics based on other properties that are easier to measure at a network level.

It is widely recognized that surface texture is the primary pavement property controlling skid resistance *(2)*. Highway texture is classified into three main categories based on a range of wavelengths and amplitudes *(3)*. The first category, microtexture (wavelengths lower than 0.5 mm), refers to the small-scale texture of the aggregate surface. The second category is the macrotexture (wavelengths of 0.5 to 50 mm), which refers to the large-scale texture of the pavement surface due to the aggregate particle size and arrangement. The third category, megatexture, has wavelengths in the same order of size as the tire-pavement interface (50 to 500 mm). The microtexture and the macrotexture are the two key pavement surface characteristics necessary for the development of good skid resistance. It is commonly accepted that microtexture controls the wet and dry friction at low speeds, while the macrotexture controls the friction at high speeds *(4)*.

A conventional approach to describe the influence of pavement texture on surface friction is using empirical modeling *(4)*. However, due to the limitations for measuring small wavelengths, many of the texture and friction relations have been implemented using only macrotexture *(5, 6, 7)* or a surrogate measure of microtexture *(8)*. Thus, the individual effects of each texture component have not been quantified, and their contribution to skid under different conditions of moisture, speed, and highway conditions are not well understood. The research on the effect of incorporating both texture component into the friction models is limited.

Recent developments in optics and computers allowed the collection of high definition images of the surface of the highway pavement. Some researchers have attempted to incorporate microtexture to the skid resistance prediction using non-contact technologies to characterize microtexture. For example, Li et al. *(9)*, Serigos et al. *(10)*, and Alhasan et al. *(11)* used laser scanners to obtain a surface profile that included microtexture wavelengths. However, the main challenge remains in the surface characterization. Currently, there are no standardized methods for microtexture characterization, and some macrotexture parameters are too simplistic and do not describe the distribution of the profile, which is critical for assessing friction characteristics.

The principal objective of this research is to investigate the effect of different texture components and their parametric description on the skid resistance of a pavement surface. We implemented a Line Laser Scanner (LLS) to make an improved characterization of the road texture,

including macrotexture and microtexture descriptions, and we used signal processing techniques to separate the effect of the different texture components. The methodology consists of field measurements of friction and texture on different surfaces on the Texas highway network using various technologies. The friction characterization tests include the British Pendulum test (BPT), the Dynamic Friction test (DFT), and the micro-GripTester. Furthermore, we evaluated and compared distinct surface texture parameters to determine the better predictors of friction.

The main contributions of the present paper are: (1) the evaluation of the effect of predicting skid resistance using both macrotexture and microtexture components obtained from field data collection; (2) the comparison of friction measures obtained using different test methods (BPT, DFT, and micro-GripTester); (3) the quantification of different macrotexture and microtexture parameters to determine the better predictor of friction; and (4) the evaluation of texture and friction characteristic of different surface types.

The subsequent sections of this paper are organized as follows. The "Background" section provides a description of the friction and texture concepts and measuring methods. "Methodology" describes the implementation of the LLS and the field data collection process. The "Statistical Analysis" section describes the data analysis technique, the models evaluated, and the statistical analysis we performed. "Results and Discussion" presents the main results and a discussion of the results. The final section, "Summary and Conclusions," summarizes the main findings.

BACKGROUND

This section provides definitions for friction and texture, as well as the description of most common methods used to measure and test these surface properties.

Friction and Skid Resistance

Pavement friction is the force that resists the relative motion between a vehicle tire and the pavement surface *(4)*. Skid resistance is the ability of the traveled surface to prevent the loss of tire traction *(12)*. The skid resistance is commonly quantified by the coefficient of friction multiplied by 100 and reported as skid number (SN). There are two types of friction that are usually measured: the side forced friction and the longitudinal friction. Several different friction-measuring devices have been developed based on the main principle of a rubber element sliding over the road surface and measuring the reaction force. The three major operating principles of frictional measurement equipment are *(13)*: slider, longitudinal friction coefficient (LFC), and side force coefficient (SFC). It should be noted that friction is not a unique value as it depends on many different variables that affect the interaction between the tire and the pavement surface.

The slider principle covers devices used for stationary testing; therefore, they are mainly used in the laboratory or require traffic control. The most commonly used devices worldwide are the British Pendulum Test (BPT) and the Dynamic Friction Test (DFT). The BPT is manually operated and provides a spot measurement of the surface friction. It measures the friction coefficient at a skidding speed of approximately 10 km/h *(14)*. Therefore, it evaluates the skid resistance at low speed. The DFT is a modular system that is controlled electronically to measure friction by the rotating principle. It measures the torque necessary to rotate three rubber sliders in a circular path at different speeds. Results are typically recorded at a range of speeds from 10 to 80 km/h, and the speed versus friction relationship can be obtained *(12)*.

Pulled devices methods utilize one or two test tires to measure pavement friction properties using the LFC or SFC principles. The locked-wheel test is the most commonly used method for measure longitudinal pavement friction at high-speed in the United States *(4, 14)*. This method is meant to test the frictional properties of the surface under emergency braking conditions for a

vehicle without anti-lock braking system (ABS). The fixed-slip techniques measure friction experienced by cars with ABS. Examples of the fixed-slip tester are the GripTester and the micro-GripTester. They can measure continuously and dynamically the longitudinal skid resistance coefficient of the pavement, expressed as Grip Number (GN). They have a single measuring wheel, fitted with a particular smooth tread tire that is mounted on an axle instrumented to measure both the horizontal drag force and the vertical load force *(15)*. The GripTester is towed behind a vehicle, and its measuring speed ranges from 5 to 100 km/h. The micro-GripTester is performed manually at a recommended walking speed of 2.5 km/h.

Texture

Pavement texture is the most important feature of the pavement surface that ultimately determines most tire-pavement interactions, including friction, noise, splash-and-spray, rolling resistance, and tire wear *(14)*. Different equipment and techniques are used to quantify texture depending on the component being measured.

Measuring Texture of Pavement Surfaces

The macrotexture is commonly described by indirect measures using volumetric techniques, such as the Sand Patch, the Grease Patch or the Outflow Meter. The Sand Patch test is known as the classical macrotexture measure technique. The method requires the use of solid glass spheres or Ottawa natural silica sand. The sand is spread on a pavement in a circular motion with a spreading tool. The known volume of sand divided by the area of the circle is reported as the Mean Texture Depth (MTD), resulting in a measurement representing an area.

Advances in technology allow the direct measure of the texture profiles using non-contact lasers, such as the Circular Track Meter (CTM) and the Laser Texture Scanner (LTS). The information collected can be used to compute various profile statistics, for example, the Mean Profile Depth (MPD). The MPD is a line measurement that is estimated by splitting the texture profile into segments of 100 mm in length. The segment is divided into two halves, and the height of the highest peak within each half is determined. The average of these two peaks is referred to as the mean segment depth. The average value of the mean segment depth of the measured profiles is the MPD. Therefore, while MPD is a one-dimensional measurement (linear property), MTD is a two-dimensional measurement (surface property).

Currently, there are no standard methods to measure microtexture. Research on the measurement of microtexture is mainly based on the use of laser scanners *(9, 10, 11)* or image analysis technique such as the Aggregate Imaging System (AIMS) *(16)*. Although, due to issues with field measurement of microtexture and its high correlation with low-speed friction, low-speed friction test measures are commonly used as a surrogate for quantifying microtexture *(8)*.

Texture Characterization

The characterization of texture consists of the use of summary statistics usually referred to as parameters. For macrotexture characterization, there are several well-defined and widely used parameters; the most common are the MPD and MTD. In the pavement engineering literature, there are no standardized methods for microtexture characterization; however, different parameters are described to characterize microtexture, including those used to describe macrotexture. The development of new equipment for digitizing surfaces allows the implementation of a series of experimental characterization procedures. Recent evaluations have focused on the study of several different spatial parameters, and the incorporation of spectral analysis to describe the texture.

Spatial parameters can be obtained in two dimensions (2D) from a linear profile, or in three dimensions (3D) from a surface profile. 2D parameters are predominant in pavement texture characterization since the data collected mainly consist of linear profiles. However, some

researchers have recently started to use 3D parameters *(17, 18)*. Spatial texture parameters are divided into four groups: amplitude, hybrid, spacing, and functional parameters. Amplitude or height parameters involve the statistical distribution of height values along the *Z-axis*. Spacing parameters include the spatial periodicity of the data. The hybrid property is a combination of amplitude and spacing. The functional parameters give information about the surface structure, based on the material bearing ratio curve.

Table 1 summarizes some of the parameters commonly used for characterization of pavement texture. The root mean square (RMS) value is used in Mechanical Engineering when a more accurate measurement of surface texture is required. Some researchers implemented RMS in highway texture description *(9, 10, 17, 19)* because it can be used along with the MPD to identify surfaces with positive or negative texture, which cannot be deduced from measurements of only MPD or MTD. Additionally, values of Skewness (R_{sk}) and Kurtosis (R_{ku}), offer a good description of the surfaces regarding the height distribution. Skewness represents the degree of symmetry of the profile heights about the mean plane. The sign of skewness indicates the predominance of peaks (positive), or valleys (negative). Kurtosis indicates the presence of extremely high peaks or depth valleys (higher than 3), or the lack of them (lower than 3). If the profile heights follow a normal distribution, the value of skewness is 0, and the value of kurtosis is 3.

Researchers have also used hybrid parameters to describe pavement surface texture *(9, 10)*. For instance, the two points slope variance (SV_{2pts}) which measures the slope between two consecutive points as the difference in height between two consecutive coordinates, divided by the horizontal distance between them. Also, the six points slope variance (SV_{6pts}), which calculates the slope using a weighted sum of the height values of six coordinates divided by the horizontal distance between them.

TABLE 1 Texture Parameters Used for Pavement Texture Characterization

Amplitude	
Mean Profile Depth (MPD)	$MPD = \frac{1}{2}\left[\max\left(h_1,..,h_{N/2}\right) + \max\left(h_{N/2+1},..,h_N\right)\right]$
Height Average (R_a)	$R_a = \frac{1}{N}\sum_{i=1}^{N}\lvert h_i\rvert$
Maximum Height (R_z)	$R_z = \max(h_i) - \min(h_i),\ \ i = 1..N$
Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} h_i^2}$
Skewness (R_{sk})	$R_{sk} = \frac{1}{RMS^3}\sqrt{\frac{1}{N}\sum_{i=1}^{N} h_i^3}$
Kurtosis (R_{ku})	$R_{ku} = \frac{1}{RMS^4}\sqrt{\frac{1}{N}\sum_{i=1}^{N} h_i^4}$
Hybrid	
Two Points Slope Variance (SV_{2pts})	$SV_{2pts} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{h_{i+1}+h_i}{\Delta x}\right)^2}$
Six Points Slope Variance (SV_{6pts})	$SV_{6pts} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{h_{i+3}-9*h_{i+2}+45*h_{i+1}-45*h_{i-1}+9*h_{i-2}-h_{i-3}}{60*\Delta x}\right)^2}$

Where, h_i = height value for coordinate "i"; N = number of coordinates; and Δx = horizontal distance between coordinates

METHODOLOGY

The methodology section describes the LLS development and data processing and presents the field data collection procedure.

LLS Development

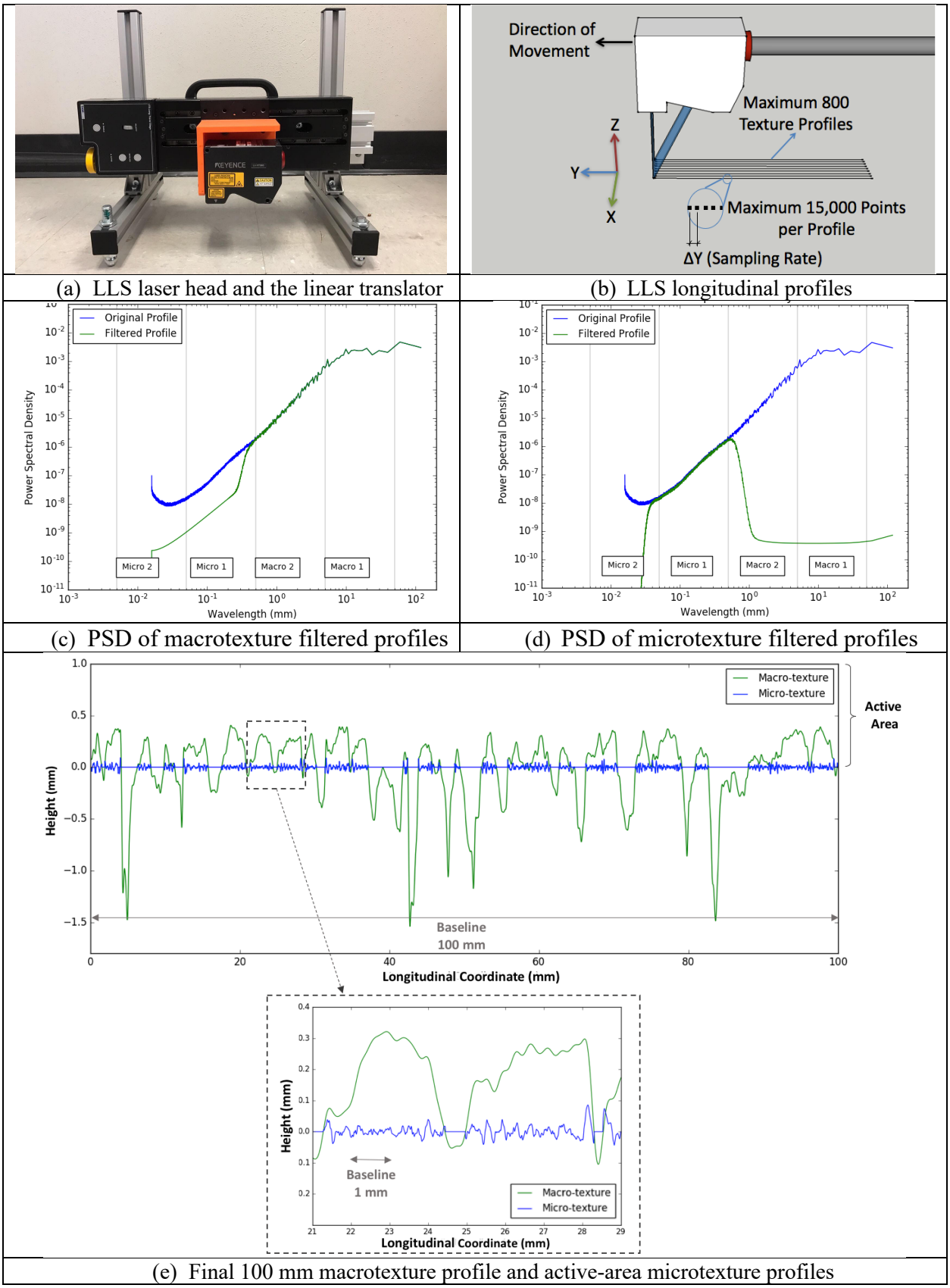
As part of this research effort, we implemented a laser scanner equipment (called LLS) to obtain higher-definition of the surface texture. The LLS consists of a line laser head and a linear translator system to control its displacement (*Y-axis*), as shown in Figure 1 (a). Also, we developed a methodological framework to collect texture information using the LLS to characterize both macrotexture and microtexture.

The LLS captures the relative-height[1] information of up to 800 profiles in 15 seconds which can be further processed and analyzed to provide a description of the texture. Each profile consists of up to 15,000 data points. The transversal direction is time-independent since the 800 points are captured instantly. The longitudinal direction is time-dependent because the 15,000 points are captured during a period that depends on the laser's sampling frequency. The sampling rate (ΔY) is given by the selected sampling frequency and the linear translator speed. In this study, we used a laser's sampling frequency of 1 kHz and a linear translator speed of 8 mm/s. Thus, the sampling rate is 8 μm, and the total covered area is 120 x 3.26 mm. The analysis is focused on the longitudinal profiles with total length of 120 mm. Figure 1 (b) provides a description of these profiles.

The laser repeatability (lower than 2 μm for the *Y-axis*) allows covering the whole macrotexture wavelength range and the first decade of microtexture. In the data processing step, we used Fourier Transform (FT) to convert the signal/data (texture profiles) from the space domain to the texture frequency (or wavelength) domain and to analyze the separate effect of each texture component. The FT transforms the texture profiles into a sum of sinusoidal waves. The output consists of the amplitudes corresponding to each texture frequency. This information can be displayed in a Power Spectral Density (PSD) plot, in which the square of the amplitude is plotted against its corresponding frequency. It can be interpreted as the power or "energy" of a signal (in this case texture) in a specific frequency or wavelength.

The relative-height distance obtained by the LLS is transformed to profile height by normalizing with respect to the best-fit line of each profile, a process also known as "detrending." Thus, the profiles are normalized with respect to an average height set equal to zero. After this process, we transform the data to the frequency domain using Discrete FT and then we filter the macrotexture and microtexture information independently using a Butterworth linear filters. The Butterworth filters were designed to be as close as possible to the ideal filter using Python coding language. We used a low-pass filter to isolate macrotexture wavelengths and a band-pass filter to isolate microtexture wavelengths. Figure 1 (c) presents the PSD of the original profile and the low-pass filtered macrotexture, while Figure 1 (d) presents the band-pass filtered microtexture profile. Further details can be found on Zuniga-Garcia *(20).*

[1] The height information depends on the laser head vertical position. The captured information corresponds to heights relative to the laser head.



(a) LLS laser head and the linear translator

(b) LLS longitudinal profiles

(c) PSD of macrotexture filtered profiles

(d) PSD of microtexture filtered profiles

(e) Final 100 mm macrotexture profile and active-area microtexture profiles

FIGURE 1 LLS setup and data processing description

The macrotexture characterization was based on a baseline of 100 mm, while a baseline of 1.0 mm was used for microtexture based on findings from previous research (10). We applied the microtexture characterization only to the contact area, which was defined as the tire-pavement interaction area. This contact or "active" area is estimated as the portion of the surface above the mean height of the profiles. Since the profiles were normalized with respect to the average height, the active area corresponds to the positive macrotexture heights. The final profiles obtained are shown in Figure 1 (e). The profiles were then characterized using the different parameters showed in Table 1 for the macrotexture and the microtexture independently. The median value of the parameters obtained for all the baseline-segments was used in the analysis.

Data Collection Procedure

We collected field measurements of friction and texture in the Texas highway network using different tests methods. The friction characterization tests included BPT, DFT, and micro-GripTester, while, the texture characterization tests comprised LLS and CTM. The test sections included a broad range of friction coefficients and texture characteristics. This variety allows a more robust study because it evaluates the relation between texture and friction on different types of pavements and represents the real heterogeneity conditions of a road network. The total number of field samples was twenty-four, including different hot mix asphalt (HMA)[2] surfaces types aged between 6 to 13 years old: dense-graded Type C (4 samples), Type D (6 samples) and Type F (2 samples), porous friction course (PFC) (8 samples), Novachip (2 samples), stone matrix asphalt (SMA) Type C (2 samples).

Sampling Method

The sampling method for the data collection in the field sections consisted of measures of the right wheel path and the center of the outer lane. We collected three different measurements at each section, with a separation of 15 m, as shown in Figure 2 (a). The results reported consisted of the average of the three replicates for the center lane and the right wheel path.

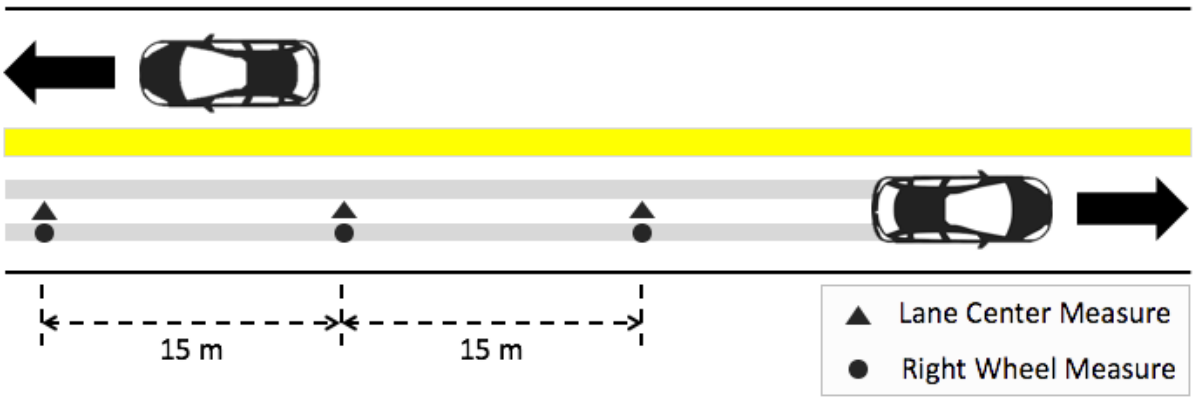
Texture Data Collection

The LLS measurements were made in the same area covered by the CTM. It was located in the sectors A and E of the CTM circumference, corresponding to the traffic direction. The results reported by the LLS consisted of the average of the two measures (sector A and E).

Friction Data Collection

The friction characterization consisted of three different friction tests. The BPT was applied in each of the sampling sites following the traffic direction, as shown in Figure 2 (b). The micro-GripTester, presented in Figure 2 (c), collects a continuous line of frictions measure. The results consist of a series of friction measures, expressed as GN, along the distance evaluated. The GN for each sample was obtained as the average of the GN measures along the total evaluated distance (approximately 30 m). The results obtained from the DFT, shown in Figure 2 (d), are used to estimate the surface friction at different speeds. Two speeds were selected to describe the DFT number (DFTN) at 20 km/h (DFT20), and 60 km/h (DFT60). These parameters were estimated as the average DFTN of the selected speed and a range of values within ±5 km/h. For instance, DFT20 is obtained as the average of DFTN values from a range of speed of 15 to 25 km/h. The use of the average instead of a single value provides a more robust analysis and increases the confidence in the results.

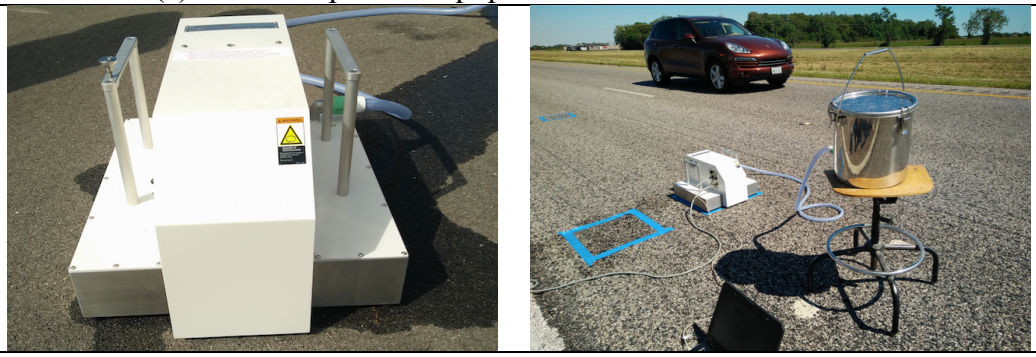
[2] For details about the HMA specifications refer to TxDOT *(21)*.



(a) Field test sampling method

(b) British Pendulum Tester (BPT) equipment and field data collection

(c) Micro-GripTester equipment and field data collection



(d) Dynamic Friction Test (DFT) equipment and field data collection

FIGURE 2 Field data collection process

STATISTICAL ANALYSIS

This section presents the statistical methods used to analyze the collected information with the objective of model friction using macrotexture and microtexture information.

Panel Data Analysis

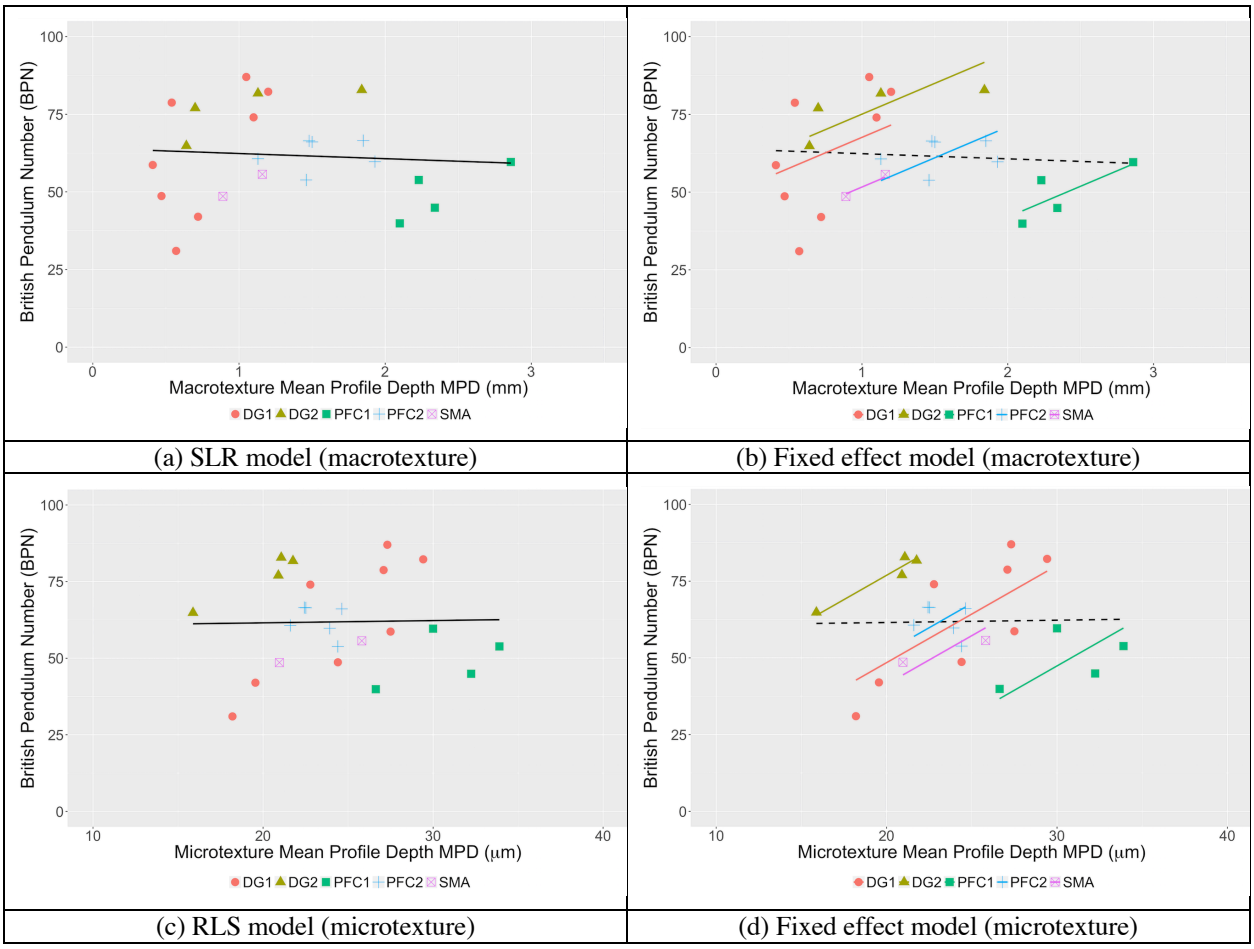
From the experimental results, we observed that a simple linear regression (SLR) analysis was not appropriate to model friction because when pooling all the texture data, the correlation between texture and friction was not significant. As an example, Figures 3 (a) and 3 (c) show the friction information obtained from the BPT and the texture represented as MPD value (derived from the LLS) modeled with SLR. We can observe that there is not a significant relationship between the dependent value friction and the independent value, texture. However, the disaggregation of the data by surface type showed a more appropriate relation with positive correlations, as expected based on the theoretical knowledge.

Therefore, an SLR analysis cannot be used for the purpose of modeling friction based on the available texture data. A better relation was found when accounting also for the surface type. This fact suggests that it is necessary to include an additional dimension in the analysis. For this reason, a panel data analysis was proposed. A panel data refers to multi-dimensional data including information about multiple phenomena (cross and longitudinal data). The panel data analysis incorporates the use of multiple regression analysis (MRA) and allows the inclusion of the surface type information into the friction model. We use the fixed effect model that considers heterogeneity across surface-type groups and keeps "fixed" (holds constant) the average effect of the texture.

We aggregated the samples by surface type and conformed five different HMA homogeneous groups. The first two groups include PFC samples because we divided them into two groups. The PFC pavements tend to present a variety of surface differences depending on the type of asphalt used, age, weather, maintenance, among other factors. The two observed PFC clusters were separated as PFC_1 and PFC_2, since they presented different macrotexture measures, although there is no further information about the characteristics of the surfaces. The first group includes the "coarse" PFC (PFC_1) because its macrotexture was greater than the PFC_2. The second group includes the "fine" PFC sample (PFC_2) and the Novachip mix since it is considered a porous friction course and its macrotexture was similar to the PFC_2 group. The dense-graded mixes were separated into two groups based on the maximum aggregate size. The first group contains the fine mixes Type D and F, and the second group is the coarse mix Type C. The five group are summarized as follow:

- Type 1 (PFC_1): Porous friction course 1
- Type 2 (PFC_2): Porous friction course 2 and Novachip
- Type 3 (DG_1): Dense-graded Type C
- Type 4 (DG_2): Dense-graded Types D and F
- Type 5 (SMA): Stone matrix asphalt Type C

The proposed analysis includes the use of the fixed effect friction model using texture information and HMA-types. The HMA-types are categorical (or qualitative) variables. Thus, they are incorporated into the models using indicator variables whose possible values are 0 and 1. The variable takes a value of 1 when the sample belongs to the proposed HMA-type, and a value of 0 otherwise. Figures 3 (b) and 3 (d) present a comparison of the SLR model (dashed lines) with the fixed effect model. We can observe that we have a constant slope in each case, corresponding to the texture effect, and we have different y-axis intersection values for each HMA group.



(a) SLR model (macrotexture) (b) Fixed effect model (macrotexture)

(c) RLS model (microtexture) (d) Fixed effect model (microtexture)

FIGURE 3 SLR and fixed effect models for BPN as a function of the MPD.

Friction Models

We proposed three friction models to evaluate the texture effect on friction measures, presented in Equations 1 to 3. The Model 1 considers only the macrotexture and HMA-type information for the independent variables *X's*. Therefore, the result of the coefficient β_{Macro} indicates the influence of the macrotexture over the friction measure, represented by the dependent variable Y_{Fr}. Similarly, for the Model 2, the β_{Micro} specifies the impact of the microtexture over the friction test. The Model 3 includes the coefficients for both macrotexture and microtexture. In this case, the model denotes the effect over the friction measure prediction when incorporating the information of the two texture components studied. The coefficient values of the indicator HMA-type variables (β_1, β_2, β_3, and β_4) capture the difference between the friction of the evaluated type with respect to the friction of Type 5 when using a fixed texture parameter value. The β_0 represents the intercept of Type 5 with the *Y-axis*, this variable does not have any significant meaning.

The three basic models were applied using the four friction measurements obtained from the tests methods as the dependent variable: BPN, GN, DFT20, and DFT60. Additionally, the texture measurements include the results obtained from the LLS for both macrotexture (X_{Macro}), and microtexture (X_{Micro}). The texture information contained in the models corresponds to the eight parameters obtained from the LLS for each texture component: MPD, RMS, R_a, R_z, R_{sk}, R_{ku}, SV_{2pts}, and SV_{6pts}. We estimated the models using the Software R and the combination of variables give a total of 96 models.

Model 1 (macrotexture only) $$Y_{Fr} = \beta_0 + \beta_{Macro}X_{Macro} + \sum_{i=i}^{4} \beta_i X_{Type\ i} \quad (1)$$

Model 2 (microtexture only) $$Y_{Fr} = \beta_0 + \beta_{Micro}X_{Micro} + \sum_{i=i}^{4} \beta_i X_{Type\ i} \quad (2)$$

Model 3 (both macro and micro) $$Y_{Fr} = \beta_0 + \beta_{Macro}X_{Macro} + \beta_{Micro}X_{Micro} + \sum_{i=i}^{4} \beta_i X_{Type\ i} \quad (3)$$

Where,
Y_{Fr} = friction measure (BPT, GN, DFT20, or DFT60).
X_{Macro} = macrotexture parameter (MPD, RMS, R_a, R_z, R_{sk}, R_{ku}, SV_{2pts}, or SV_{6pts}).
X_{Micro} = microtexture parameter (MPD, RMS, R_a, R_z, R_{sk}, R_{ku}, SV_{2pts}, or SV_{6pts}).
i = surface type index (Type 1, Type 2, Type 3, or Type 4).
$X_{Type\ i}$ = dummy variable equal to 1 if the mixture is Type i and 0 otherwise.

Hypothesis Test

We used a two-tailed hypothesis test to determine if the independent variables included in the models (texture and HMA-type) had a statistically significant influence on friction. The confidence level selected was 95%, i.e., a significance level $\alpha = 0.05$. The null hypothesis (H_0), Equation 4, establishes that the coefficient (β_i) was equal to 0, meaning that the corresponding independent variable did not have any impact on the friction. The alternative hypothesis (H_a), Equation 5, states that the coefficient is distinct from 0, which means that the variable did have a statistically significant influence on friction. The null hypothesis needs to be rejected to be able to conclude that the coefficients are different than 0 and that the corresponding independent variable has a statistically significant influence on the friction with a confidence level of 95%.

$$H_0: \beta_i = 0 \quad (4)$$

$$H_a: \beta_i \neq 0 \quad (5)$$

Where, i = Macro, Micro, Type 1, Type 2, Type 3, and Type 4.

For the hypothesis testing, we analyzed information about the t-static and p-value for each coefficient value. These two indicators determine whether to reject or not the null hypothesis. The t-statistic is a ratio of the departure of an estimated parameter from its notional value and its standard error. The p-value (or observed significance level) represents the probability, assuming that the null hypothesis is true, of obtaining a value of the t-statistic at least as contradictory to the null hypothesis as the value calculated from the available sample.

We use the p-value to make the final decision of rejecting or not the null hypothesis by comparing it with the significance level (α), which is the probability of rejecting the null hypothesis when true (type I error). The p-values must be lower than $\alpha = 0.05$ to reject the null hypothesis. The SLR models use the coefficient of determination (R^2), as a comparison measure of which model has a higher correlation between *Y* and *X* values, since it measures how close the data are to the fitted regression line. However, the R^2 is not an appropriate parameter to compare MRA models, because its value increases every time an additional predictor variable is added to the model. The coefficient of multiple determination (R_{adj}^2) adjusts the R^2 for the number of predictor variables in the model. Thus, this indicator is more appropriate to compare models with a different number of independent variables. For this reason, we obtained the R_{adj}^2 for all the models analyzed in this study.

RESULTS AND DISCUSSION

In this section, we present the primary results and provide the discussion that leads to the main findings. We first analyze the fiction models including only the MPD as a texture parameter and then evaluate the models that used the other seven parameters.

Using the MPD as Texture Parametric Description

The MPD is the most widely used macrotexture parameter. For this study, we estimated the macrotexture MPD value using the LLS and compared the results with the CTM, which also provides macrotexture MPD results. The correlation between both values, measured using the correlation coefficient R^2, is 95% which is considered high. The rest of the analysis includes the MPD based on the LLS only.

We estimated the Models 1 to 3 using R software and collected the more relevant information. We modeled friction using the four different friction measures and utilized texture as predictor using the MPD as the parameter for both macrotexture and microtexture. Table 2 shows the results for the t-statistic and p-value for the models' coefficients of interest (β_{Macro} and β_{Micro}), and the R_{adj}^2 for the friction models. The shaded t-statistic and p-values represent the conditions of failing to reject the null hypothesis. Also, Figure 4 presents these results in graphical representation for Models 1 and 2.

TABLE 2 Statistical Analysis for the Friction Models Using MPD

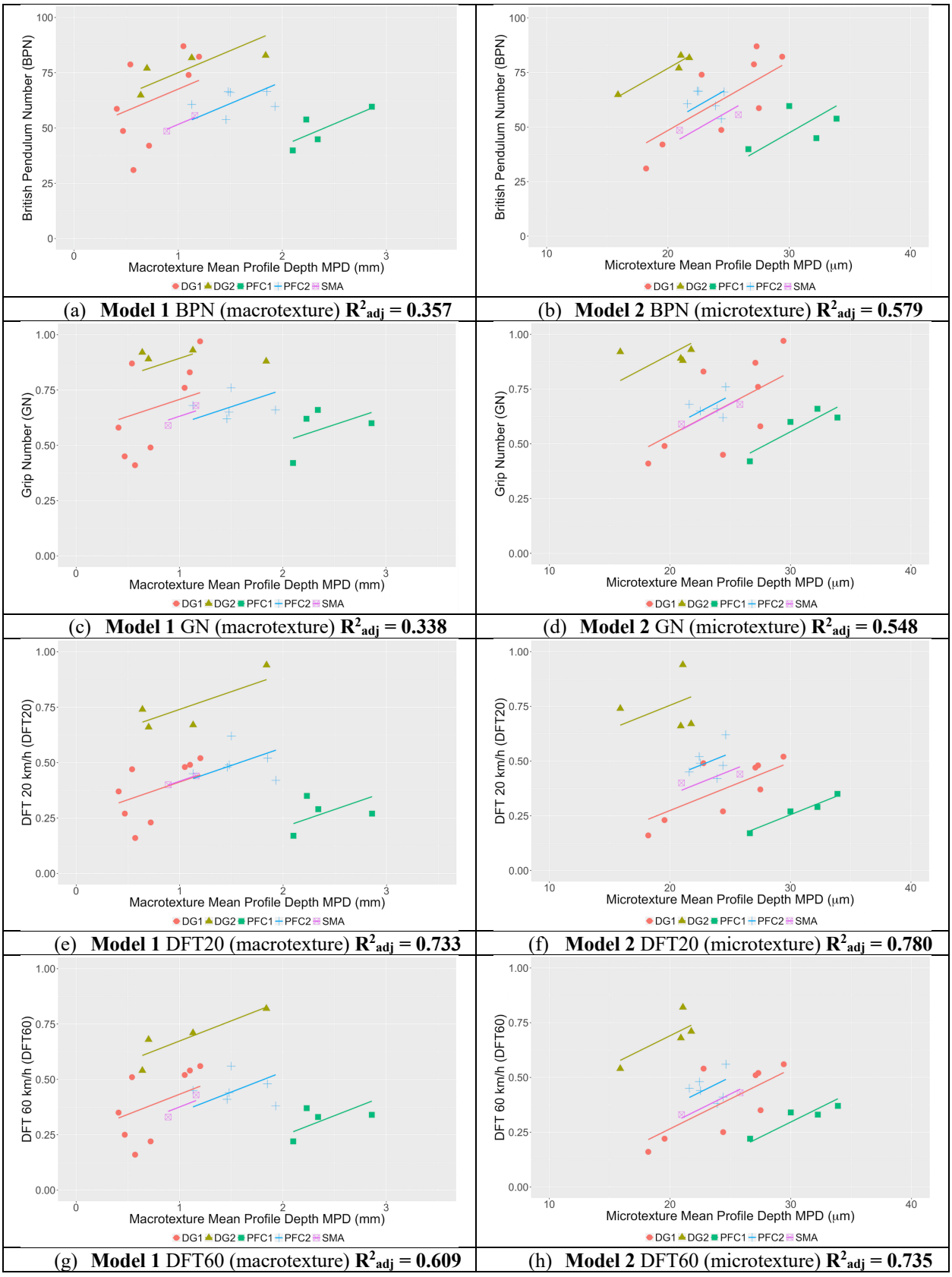
Friction Model	Friction Measure											
	British Pendulum Number (BPN)			*Grip Number (GN)*			*Dynamic Friction Test 20 km/h (DFT20)*			*Dynamic Friction Test 60 km/h (DFT60)*		
	β	t-stat (p-value)	R^2_{adj}	β	t-stat (p-value)	R^2_{adj}	β	t-stat (p-value)	R^2_{adj}	β	t-stat (p-value)	R^2_{adj}
Texture parameter: **Mean profile depth (MPD)**												
1-Macro only	β_{macro}	2.533 (0.021)	**0.357**	β_{macro}	1.709 (0.106)*	**0.338**	β_{macro}	2.602 (0.018)	**0.733**	β_{macro}	2.786 (0.012)	**0.609**
2-Micro only	β_{micro}	4.397 (0.000)	**0.579**	β_{micro}	3.491 (0.003)	**0.548**	β_{micro}	3.479 (0.003)	**0.780**	β_{micro}	4.472 (0.000)	**0.735**
3-Both macro and micro	β_{macro} β_{micro}	2.135 (0.048) 3.996 (0.001)	**0.649**	β_{macro} β_{micro}	1.047 (0.310)* 3.008 (0.008)	**0.551**	β_{macro} β_{micro}	2.136 (0.048) 3.034 (0.007)	**0.816**	β_{macro} β_{micro}	2.487 (0.024) 4.148 (0.000)	**0.794**

* Note: the shaded t-statistic and p-values represent the conditions of failing to reject the null hypothesis (|t-stat|<|1.96| and/or p-value>0.05).

BPT and MPD Parameter

Based on the results using BPN as the dependent variable, the Model 1 suggests that the macrotexture has a statistically significant influence on friction. Utilizing the t-statistic and p-value, we can reject the null hypothesis. Similarly, Model 2 indicates that microtexture influences friction. This finding is significant because it proves, with field information, that both macrotexture and microtexture, represented by the MPD, have a statistically significant impact on the friction measured with the BPT. Also, it is important to mention that the R_{adj}^2 is nearly 60% greater for the Model 2 (microtexture) than for the Model 1 (macrotexture). This fact suggests that the microtexture have a more significant impact to the BPT friction than the macrotexture, which is consistent with the theory since at low speeds the microtexture effect is dominant, due to the adhesion mechanism.

The results for Model 3 show that both macrotexture and microtexture affect friction and that by including both components into the model, the R_{adj}^2 increased to 0.649, compared to Model 1 (0.357) and Model 2 (0.579), where only the individual effects were incorporated. Thus, Model 3 is the best model to describe friction obtained by the BPT, using the MPD parameter.



(a) **Model 1** BPN (macrotexture) $\mathbf{R^2_{adj} = 0.357}$

(b) **Model 2** BPN (microtexture) $\mathbf{R^2_{adj} = 0.579}$

(c) **Model 1** GN (macrotexture) $\mathbf{R^2_{adj} = 0.338}$

(d) **Model 2** GN (microtexture) $\mathbf{R^2_{adj} = 0.548}$

(e) **Model 1** DFT20 (macrotexture) $\mathbf{R^2_{adj} = 0.733}$

(f) **Model 2** DFT20 (microtexture) $\mathbf{R^2_{adj} = 0.780}$

(g) **Model 1** DFT60 (macrotexture) $\mathbf{R^2_{adj} = 0.609}$

(h) **Model 2** DFT60 (microtexture) $\mathbf{R^2_{adj} = 0.735}$

FIGURE 4 Friction fixed-effect models using macrotexture MPD and microtexture MPD

Micro-GripTester and MPD Parameter

The results from MPD and the GN from Table 2 show that using macrotexture information (Model 1), the null hypothesis $\beta_{Macro-MPD} = 0$ cannot be rejected. Therefore, the model suggests that the friction cannot be predicted using macrotexture information for the micro-GripTester. However, the Model 2 shows that the microtexture has an effect on GN ($\beta_{Micro-\ MPD} \neq 0$). Also, the results show that the friction prediction is not improved by incorporating both macrotexture and microtexture information since the Model 3 presents a similar R_{adj}^2 than Model 2, and the $\beta_{Macro-MPD}$ does not have statistical significance. Therefore, the Model 2 is the most appropriate for the micro-GripTester measures. These results can be related to the speed of the test (2.5 km/h). It is apparent that this test is not capturing macrotexture influence due to the low speed.

DFT and MPD Parameter

The DFT allows an evaluation of the relationship texture-friction at a range of speeds. As stated previously, for the present study only two speeds were selected, 20 and 60 km/h. The two cases present t-statistics and p-values that allow the rejection of the null hypothesis, supporting the notion that $\beta_{Macro-MPD} \neq 0$ and $\beta_{Micro-MPD} \neq 0$. Therefore, both macrotexture and microtexture have an influence on the friction obtained from the DFT.

The results from the DFT models present values of R_{adj}^2 greater for the Model 2 compared to Model 1, approximately 7% (DFT20) and 19% (DFT60) more. Thus, for all the cases the Model 2, which includes only the microtexture, has a better correlation coefficient than Model 1 that only includes the macrotexture. Also, the results show that the Model 3 is the most appropriate model since it presents the higher R_{adj}^2. The Model 3 includes the information of both macrotexture and microtexture. The greater R_{adj}^2 obtained is 0.816, corresponding to Model 3 when using DFT20 as the dependent variable.

Evaluation of Different Texture Parameters

We evaluated the same models using seven different texture parameters. Table 3 summarizes the results. In this case, we select only the models that performed better for each friction measure. For instance, we show Model 3 for the BPT and the DFT measure and Model 2 for the GN measure. Based on the results, only the R_z parameters have statistical significance for the GN and the DFT measures, similar to the effects observed for the MPD parameter. It is important to mention that the MPD and the R_z were obtained with a similar methodology. Therefore, is likely that these two parameters present comparable results. For instance, the R_{adj}^2 value is similar for the models using these two parameters. However, only the MPD models reject the null hypothesis for both β_{Macro} and β_{Micro} from Model 3 for the BPT measure.

The other six parameters do not seem to provide a good correlation with the friction measures. Only the parameters R_a, RMS and SV_2, and SV_6 offer significant models for the GN values but not for the BPN and DFT values. The results obtained were not expected because the MPD and the R_z measure very simplistic characteristics of the profiles, while parameters such as the SV and R_{sk} provide more details about the height distribution. Thus, we expected a better friction correlation. However, based on the evidence obtained in this study, the MPD appeared to be the better texture characterization parameter to model friction.

TABLE 3 Statistical Analysis for the Friction Models Using Different Texture Parameters

Friction Measure											
British Pendulum Number (BPN)			*Grip Number (GN)*			*Dynamic Friction Test 20 km/h (DFT20)*			*Dynamic Friction Test 60 km/h (DFT60)*		
Model 3-Both macro & micro			**Model 2**-Micro only			**Model 3**-Both macro & micro			**Model 3**-Both macro & micro		
β	t-stat (p-value)	R^2_{adj}	β	t-stat (p-value)	R^2_{adj}	β	t-stat (p-value)	R^2_{adj}	β	t-stat (p-value)	R^2_{adj}
Texture parameter: **Maximum height (Rz)**											
β_{macro}	1.906 (0.074)*	**0.639**	β_{micro}	3.521 (0.003)	**0.552**	β_{macro}	1.980 (0.064)	**0.808**	β_{macro}	2.216 (0.041)	**0.787**
β_{micro}	4.009 (0.001)					β_{micro}	2.926 (0.009)		β_{micro}	4.153 (0.001)	
Texture parameter: **Height average (Ra)**											
β_{macro}	1.539 (0.142)*	**0.624**	β_{micro}	3.665 (0.002)	**0.567**	β_{macro}	1.434 (0.170)*	**0.796**	β_{macro}	1.654 (0.117)*	**0.768**
β_{micro}	4.303 (0.000)					β_{micro}	3.277 (0.004)		β_{micro}	4.408 (0.000)	
Texture parameter: **Root mean square (RMS)**											
β_{macro}	1.269 (0.221)*	**0.606**	β_{micro}	3.656 (0.001)	**0.566**	β_{macro}	1.284 (0.216)*	**0.789**	β_{macro}	1.481 (0.157)*	**0.759**
β_{micro}	4.250 (0.000)					β_{micro}	3.224 (0.005)		β_{micro}	4.361 (0.000)	
Texture parameter: **Skewness (Rsk)**											
β_{macro}	3.168 (0.006)	**0.433**	β_{micro}	0.864 (0.400)*	**0.257**	β_{macro}	2.623 (0.018)	**0.731**	β_{macro}	2.642 (0.017)	**0.595**
β_{micro}	0.534 (0.600)*					β_{micro}	0.643 (0.529)*		β_{micro}	0.735 (0.473)*	
Texture parameter: **Kurtosis (Rku)**											
β_{macro}	-4.889 (0.000)	**0.622**	β_{micro}	0.320 (0.753)*	**0.229**	β_{macro}	-3.182 (0.005)	**0.757**	β_{macro}	-3.937 (0.001)	**0.699**
β_{micro}	-0.093 (0.927)*					β_{micro}	-0.288 (0.777)*		β_{micro}	0.272 (0.789)*	
Texture parameter: **Slope variance 2 points (SV2)**											
β_{macro}	-0.048 (0.962)*	**0.429**	β_{micro}	3.050 (0.007)	**0.499**	β_{macro}	0.801 (0.434)*	**0.779**	β_{macro}	0.735 (0.472)*	**0.655**
β_{micro}	2.499 (0.023)					β_{micro}	2.151 (0.046)		β_{micro}	2.123 (0.049)	
Texture parameter: **Slope variance 6 points (SV6)**											
β_{macro}	0.159 (0.875)*	**0.458**	β_{micro}	3.267 (0.005)	**0.524**	β_{macro}	1.041 (0.313)*	**0.782**	β_{macro}	1.057 (0.305)*	**0.677**
β_{micro}	2.730 (0.014)					β_{micro}	2.258 (0.037)		β_{micro}	2.341 (0.032)	

* Note: the shaded t-statistic and p-values represent the conditions of failing to reject the null hypothesis (|t-stat|<|1.96| and/or p-value>0.05).

SUMMARY AND CONCLUSIONS

This research study addressed pavement texture characterization and modeled its influence on pavement friction. We developed a 3D laser scanner, called LLS, to measure both macrotexture and microtexture, and provided a description of the data processing techniques used to isolate the profiles. The analysis included empirical data collected around the Texas highway network using different friction devices: BPT, DFT, and micro-GripTester. Furthermore, we used eight different parameters to characterize texture and evaluated friction models using these parameters.

Among the major findings, the empirical data suggests that there is not a unique relationship between texture and friction. The relationship between texture and friction is strong, but it is different for each type of surface. Therefore, it is important to include the surface type information when modeling friction. Additionally, we found that models including microtexture present higher correlation and that incorporation both microtexture and macrotexture result in a more appropriate friction estimation. Thus, a measure of microtexture should be included into friction models based on texture. Regarding the texture parametric description, we found that the MPD was the most significant parameter for macrotexture and for microtexture to explain the distinct friction measures.

The results and methods proposed in this study can serve multiple purposes. First, from the transportation agencies point of view, the proposed models will allow the accurate estimation of friction using texture data at the network level. As of today, equipment is available to measure macrotexture at highway speed. The research team is currently working on the measurement of microtexture at highway speeds. Once these two types of information are available, the estimation of friction from texture data will be done more efficiently than running friction tests that required frequent stops to refill the water tanks. This contribution would help to manage and monitoring friction information more efficiently. While texture measurements cannot completely replace friction measurements, texture measurements, including macrotexture and microtexture, can safely be used to identify network areas that are potentially having low friction values. Second, we provide empirical evidence of the need for measuring microtexture wavelengths when characterizing pavement surface texture. With the increasing number of researchers acquiring new technology methods to describe the microtexture, there is also a need to provide standard procedures for uniform and comparable characterization techniques. Finally, our results may also have relevance in the field of transportation research. We provide an application of a panel data analysis approach that allows the incorporation of other variables into the models to account for heterogeneity across surface types and provide a more robust analysis.

Based on the results of this research study, the research team is currently investigating new hardware both in term of laser technology and data processing technology in an attempt to develop equipment to capture microtexture at highway speed. On the aspect of implementation, the research team is applying the findings of this study to include a wider variety of pavement surfaces and friction measuring techniques. Also, we recommend an evaluation using the Locked Wheel Tester and the GripTester because these devices use higher testing speeds and simulate better real conditions.

Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: Natalia Zuniga-Garcia and Jorge A. Prozzi; data collection: Natalia Zuniga-Garcia; analysis and interpretation of results Natalia Zuniga-Garcia and Jorge A. Prozzi; draft manuscript preparation: Natalia Zuniga-Garcia. All authors reviewed the results and approved the final version of the manuscript.

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