Use of Digital Image Modeling for Evaluation of Concrete Pavement Macrotexture and Wear

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Abstract

Modeling of the pavement image formation process using reflection properties of macrotexture showed that digital images of concrete pavements can be used to monitor pavement wear. The specific optical characteristics of images and the optimum camera settings that can be used for this purpose were determined by theoretically formulating the Bidirectional Reflection Distribution Function (BRDF) of surface texture with uniform color. In the analytical phase of the study, desired levels of pavement texture were generated by combining a series of 3-D sine surfaces of varying wavelengths and amplitudes. The optimum specular settings of the overhead point light source and the digital area-scan camera for effective highlighting of the imaged wheel path macrotexture were determined with an analytical formulation based on a simplistic and physically meaningful BRDF model. It was also shown that the images obtained by the theoretical formulation closely resemble those captured from a similarly textured experimental surface under identical lighting and imaging conditions. In particular, the pavement image formation model revealed that quantifiable changes in the brightness of images do occur due to changes in texture depth and spacing (wavelength). In the next phase of the study, the traffic induced pavement wearing process was simulated by gradual smoothening of the modeled surfaces and then images corresponding to each wearing stage were generated. The theoretically predicted variation of the image brightness due to wear was experimentally verified using images from a gradually worn out concrete specimen. Finally it was illustrated how the brightness evaluation of wheel path images has the potential to be a screening tool to monitor the degradation of macrotexture and hence the skid-resistance of pavements at the network level.

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Importance of Surface Macrotexture Evaluation in Pavement Management

A major task of pavement management is to ensure adequate skid-resistance (friction) on all pavements in a network. Gradual degradation of skid-resistance on highways and runways can be attributed primarily to pavement texture changes due to traffic induced wear. Therefore, a safe level of skid resistance can be ensured by regularly monitoring pavement texture and taking corrective measures to restore degraded texture in a timely manner. Pavement friction is known to originate from two levels of texture; (1) macro-texture (depths from 0.5 to 20 mm and widths from 0.5 to 50 mm) and (2) micro-texture (depths from 0.001 to 0.5 mm and widths less than 0.5 mm) (Table 1, ISO 1997).

The specific influence of pavement texture on skid-resistance and tire wear has been investigated by Britton et al. (1974), Leu and Henry (1978) and Balmer (1978). A single model correlating skid resistance to both macrotexture and microtexture evaluations was first introduced by Leu and Henry (1978). More recently, Gendy and Shalaby (2007) found that the complete characterization of skid resistance must involve all three attributes; size, spacing and shape of both macrotexture and microtexture. Microtexture which can be detected indirectly in the field by the British Portable Skid Tester (BPT) (ASTM E303-93 ) governs the dry friction produced by adhesion at low tire speeds. On the other hand, macrotexture produces hysteresis friction at high tire speeds and in addition reduces the possibility of hydroplaning by facilitating the drainage of water. Macrotexture can be evaluated using the mean texture depth (MTD) or the mean profile depth (MPD) (ASTM E 1845-01).

The wet skid-resistance of localized areas of highway pavements can be evaluated by the Locked-wheel Skid-Tester (LWST) at a slip speed of 65 km/hr (ASTM E 274-06), while the Runway Friction Testers (RFT), Grip testers and mu meters can be employed to evaluate the wet skid resistance continuously over limited length of runway sections at designated slip speeds. Although highway agencies have used high-speed skid testers for many years they are not suitable for network level analysis. Since the wet friction estimates vary from one device to another, the “spot-measuring” and relatively precise Dynamic Friction Tester (DFT) is considered to provide the standard friction values at a slip speed of 60 km/h (ASTM 1911-09a).
Screening of pavements with respect to skid-resistance can only be achieved with techniques that can monitor the changes in skid-resistance along an entire pavement network based on evaluating the degradation of its macro-texture in particular. The laser evaluation of macrotexture does not have the capability to determine whether the surveyed profile is formed by the pavement material itself or the deposited contaminants. However, if the laser technology is used in conjunction with a contamination detector, then the contaminated locations can be identified first. The DSC111 (http://www.laserfocusworld.com/display_article/318554/12/none/none/News/ROAD-MONITORING:-Laser-system-monitors-slipperiness-of-roadway) is a road-surface sensor that has been created using lasers and transmitter optics to obtain short-range spectroscopic measurements of the water and ice on a road surface. Using this device frost, snow, slush, and black ice on the road surface are differentiated by distinguishing between the specific wavelengths of water and ice. Therefore, the advantage of using digital images is that they can be used to first distinguish the contaminated locations from the others. The INO LCMS (www.ino.ca/Docs/Documents/publications/technical/3D-sensors) system employs high speed cameras, custom optics, and laser line projectors to acquire 2D images and high resolution 3D profiles of road surfaces that allow for automatic detection of cracks and the evaluation of macro-texture and other road surface features. The potential also exists for using only appropriately calibrated images of wheel paths to predict the corresponding changes in macro-texture and skid resistance.

**Acquisition of pavement digital images**

Pavement evaluation based on automated digital image analysis has been replacing the manual pavement evaluation due to its improved efficiency and operational safety. While linescan cameras are widely used in state-of-the art pavement evaluation vehicles to monitor the pavement distress (cracking) condition at regular time intervals (Wang 2007, Huang and Xu 2006, Mraz et. al. 2006, Amarasiri et. al. 2007), area-view digital cameras are employed for imaging roadway signs and safety features (Mraz et al, 2005). Typical highway imaging systems include an exterior light source and a digital camera and the associated acquisition, storage and the processing system mounted inside the imaging vehicle. In the latest imaging vehicles, the lamp-based artificial illumination is replaced
by laser lights to overcome the issues of non-uniform illumination and shadows. Area-
view cameras can also capture grayscale images where the optical texture variation on
the pavement surface is manifested by a wide range of pixel intensity values from 0 to
255, where 0 represents black and 255 represents white.

Most state-of-the-art cameras possess the resolution to capture a 1mm x 1mm pavement
area at each pixel level with the intensity of a pixel depending on the variation of the
profile and the color of the surface. Thus, the optical texture variation of an image due to
pavement macrotexture induced surface profile variation can be used to detect the
changes in macrotexture. The current pavement imaging technology has been limited
mostly to detection and evaluation of cracks and other distresses. The authors have not
found published evidence of any attempts to use digital images for macrotexture
detection. By applying appropriate modifications with respect to the installation of the
existing digital imaging equipment, pavement macrotexture changes can also be captured
in the images. Hence the network level evaluation of significant pavement wear and
changes in skid resistance can be facilitated by the imaging technology.

Objectives of the investigation
The focus of this paper is to theoretically model the wear induced intensity changes in
digital images of pavement locations which are deemed to be uncontaminated and
evaluate the above changes experimentally. In the preliminary study reported in this
paper, first the geometrical reflection properties of macrotexture would be used to model
the digital image formation of pavement surfaces of uniform color. Second, the above
imaging model would be used to identify (1) the changes in optical properties of digital
images that reflect pavement wear and (2) the optimum specular setting required by the
imaging system to detect the above changes. Then a simple experimental study would be
set up to verify the theoretical findings. Finally, it would be illustrated how the detectable
changes that occur in the optical properties of digital images due to the pavement wear
can be correlated to degradation of macrostructure and consequent loss of skid-resistance.
Advances in surface characterization using digital images

The identification of object characteristics from their images has been made possible by recent advances in the image processing technology. Tamura et. al. (1978) modeled optical texture of a physically textured object using its reflection properties and illustrated how it facilitates image classification, image segmentation, and image encoding. Optical texture models have also been used to recreate depth and orientation of objects and to generate desired synthetic image textures by adjusting model parameters (Tamura et. al. (1978)). It was shown by Shapiro et. al.(2001) that the optical texture of pavement images can also be formed from image primitives of varying shape or by using stochastic assumptions. In the above work, pavement macrotexture and microtexture were considered to be composed respectively of relatively large and small optical texture primitives. The intensity of each pixel in the image space has also been considered a random variable within a range of intensities defined by the neighboring pixels. Consequently, this relationship of interdependence of intensities has been modeled using the Markov random field theory to determine the pavement image texture parameters and hence evaluate the specific parameters relevant to pavement friction (Rado (1994)). Rado (1994) used the above model to correlate the macrotexture to image intensities of local neighborhoods using actual images of pavements and the corresponding mean texture depths measured from those pavement profiles.

More recently Khoudeir and Brochard (2004) have studied the changes in image properties due to wearing of pavement surfaces based on the statistical properties of the image gradient, the curvature map of the gray level images, and the derivative of the autocorrelation function of several lines of the images. However in Khoudeir and Brochard (2004) work, the intensity of light reflection in a given direction was considered to be governed by the reflected angle only thus neglecting its significant dependence on the incident angle and the surface properties. In the work presented in this paper the intensities of incident and reflected light as well as the reflection properties of surfaces of uniform color are used in modeling the wearing of pavement macrotexture.
Modeling of the pavement image formation process

Surfaces where reflection of light is limited to the exact opposite direction as dictated by the law of reflection are known as specular surfaces while surfaces that reflect light in all directions including the specular direction are termed diffusive ones. Generally most pavement surfaces have both specular and diffusive properties depending on the geometry of the surface texture formed by the material constituents. Therefore, their characteristic reflection properties can be exploited to model the images of texture and distress features of pavements.

Bidirectional Reflection Distribution Function (BRDF)

The intensity of specular and diffusive reflection (radiance) from any point on a surface must be considered as a function of the intensity of incident light (irradiance), the local reflection properties and the orientation of the surface to the direction of incidence. This complex relationship between the radiance and irradiance of a surface can be best described by the Bidirectional Reflection Distribution Function (BRDF) (Ngan et. al., 2005). BRDF of a surface is defined as the ratio of radiance in a given direction ($\vec{R}$) to the irradiance on that surface from another direction ($\vec{I}$) (Eqn. 1(a)).

$$BRDF(\vec{I}, \vec{R}) = \rho(\vec{I}, \vec{R}) = \frac{L_r(\vec{R})}{L_i(\vec{I}) \cos \theta_i \, d\omega} \quad (1a)$$

where $L_r(\vec{R})$ is the radiance (reflected flux per unit normal area per unit solid angle)

$L_i(\vec{I})$ is the irradiance (incident flux per unit normal area per unit solid angle)

$\theta_i$ is the polar angle between the incident vector and the surface normal

d\omega is the solid angle subtended at the surface point by the incident light source

The total radiance at a point on the surface in the direction $\vec{R}$ due to light entering the entire hemisphere surrounding that point can be expressed as,

$$L_r(\vec{R}) = \int_0^{2\pi} \rho(\vec{I}, \vec{R}) L_i(\vec{I}) \cos \theta_i \, d\omega \quad (1b)$$
Since, \(d\omega = \sin \theta_i d\theta_i d\phi_i\), where \(\phi_i\) is the azimuth angle of the incident vector projected on the surface plane, the 3-D form of the above relationship is based on two incident and two reflected angles defining the directions \(\vec{I}\) and \(\vec{R}\) as expressed in Eqn. 2a,
\[
L_r(\theta_r, \phi_r) = \int_0^{\pi/2} \int_0^{2\pi} \rho(\theta_i, \phi_i; \theta_r, \phi_r) L_i(\theta_i, \phi_i) \cos \theta_i \sin \theta_i d\theta_i d\phi_i
\]  
(2a)

where \(\theta_i\) is the polar angle between the reflected vector and the surface normal \(\phi_i\) is the azimuth angle of the reflected vector projected on the surface plane \(L_r(\theta_r, \phi_r)\) is the reflected radiance (watts/steradian/meter\(^2\)) \(L_i(\theta_i, \phi_i)\) is the incident radiance (watts/steradian/meter\(^2\)) \(\rho(\theta_i, \phi_i; \theta_r, \phi_r)\) is the BRDF (steradian\(^{-1}\)) given by equation 1(a)

The total radiance in the direction \(\vec{R}\) from a given point due to a single light source that subtends a solid angle of \(\Delta\omega\) on a discrete area used for computing the \(\rho\) value of that point can be obtained from Equation (1a) as;
\[
L_r(\theta_r, \phi_r) = L_i(\theta_i, \phi_i) \rho(\theta_i, \phi_i; \theta_r, \phi_r) \cos \theta_i \Delta\omega
\]  
(2b)

Traditionally the BRDF of a desired object or a surface is measured using a gonioreflectometer (Marschner et al., 2000). The most common functions that are used to represent BRDF of a surface are the tensor products of the spherical harmonics, Zernike polynomials, and spherical wavelets (Rusinkiewicz S., 1998). However, most of the above basic functions require a large number of coefficients to describe even moderately specular BRDFs. In addition, the above methods do not require any less storage even under isotropic BRDF conditions. Rusinkiewicz (1998) proposed a method for decomposing BRDFs by changing variables more efficiently. In the Rusinkiewicz (1998) transformation, the BRDF is represented in terms of half angle between incident and reflection directions, and the difference angle between the half angle and incident angle (\(\vec{h}\) in Fig. 1). Kautz and McCool (1999) used single value decomposition (SVD) and normalized decomposition (ND) for the BRDF function. On the other hand, simplified models are also available for approximate evaluation of BRDF such as Phong (1975), He (1991), Cook et al (1981), and Ward (1992) models.
Ward’s reflection model for BRDF

In the image modeling presented here, the Ward’s reflection model (Ward, 1992) is used due to its simplicity and physically meaningful parameters. Although Ward (1992) formulated reflection models for both anisotropic and isotropic surfaces, for most pavement surfaces, the isotropic model given by Equation (3a) would suffice.

\[
\rho(\theta, \phi; \theta_s, \phi_s) = \frac{\rho_d}{\pi} + \rho_s \cdot \frac{1}{\sqrt{\cos \theta \cos \theta_s}} \cdot \exp\left[-\frac{\tan^2 \delta / \alpha^2}{4\pi^2}\right]
\]  

(3a)

Where \( \rho_d \) is the diffuse reflectance of the surface (steradian\(^{-1}\))

\( \rho_s \) is the specular reflectance of the surface (steradian\(^{-1}\))

\( \delta \) is the angle between vectors \( \hat{n} \) and \( \hat{h} \) in Figure 1 (\( \hat{n} \) is the unit normal to the surface, \( \hat{h} \) is the half vector between the unit incident vector \( \hat{d} \) and unit reflection vector \( \hat{r} \) as illustrated and defined in Eqn. (3b)).

\( \hat{h} = \hat{d} + \hat{r} \)  

(3b)

\( \alpha \) is the standard deviation of the surface slope or the square root of the slope variance.

Selection of surface parameters for the reflection model

The three dominant parameters in the Ward’s reflection model (Eqn. 3a) are \( \rho_d \), \( \rho_s \) and \( \alpha \). Of these \( \alpha \) represents the changes in the surface slopes or the randomness in the orientation of tiny surface fractals that can be attributed to both macrotexture and microtexture. Therefore, at a particular pavement location, the direction of light reflection can be considered to be totally specular at the minute fractal level. Smooth surfaces that are characterized by low slope variances (\( \alpha \)) reflect light mostly in the specular direction with much lower reflection components in the other directions. As \( \alpha \) increases, more and more light reflects in the directions other than the specular direction and the surface assumes diffusive characteristics. Therefore, when the neighborhood of any point is observed as a single unit, light reflection appears to be diffusive due to the specular scattering of light caused by the differences in orientation of the multitude of tiny fractals that compose that neighborhood. The direction of scattering follows a Gaussian distribution with the variance expressed by the local slope variance \( \alpha \).
singly low $\alpha$ value such as 0.0001 (based on Eqn. 3a) defines a surface with high specularity, where as a relatively high value of $\alpha$ (ex. above 0.2) portrays a highly random fractal orientation and hence a diffusive surface for all practical purposes. However, once a limiting value of $\alpha$ is exceeded, one can expect the radiance to be curtailed in all directions due to obscurity and internal reflection caused by the interference within the surface profile itself.

In this analysis $\alpha$ was computed from the variation of surface slopes in the neighborhood surrounding the nodal point of interest. For the assumption of local specularity to be valid in the neighborhood of any node and the value of $\alpha$ to capture the microtexture, the nodal spacing was selected as 0.025 mm in both x and y directions (Table 1). In the imaging systems currently used in pavement survey vehicles manufactured by the state-of-the-art industry, the pixel resolution that corresponds to their optics and installed heights from the pavement surface, allows them to achieve a “pavement resolution” of only 1 mm. Thus, although theoretical modeling of the texture imaging can reach the microtexture level, any refinement in the fineness of the nodal mesh beyond 0.5 mm would only make the computation of nodal $\alpha$ values more accurate and produce images that show more texture details than real images. Since the reflection at each local node is considered to be specular, $\rho_s$ and $\rho_d$ (Eqn. 3a) are assigned values of 1.0 and 0 respectively.

Simulation of the pavement texture profile

In the modeling of images of pavement macrotexture, the pavement profiles were represented in terms of 3-D sine functions. This representation can be justified based on the principles of Fourier decomposition, whereby most pavement texture profiles can be approximated with a series ($n$) of finite 3-D sine waves varying in wavelengths and amplitudes as shown in Eqn. (4).

$$ z = \sum_{i=1}^{n} amp_i \sin \left( \frac{2\pi x}{\lambda_i} + \frac{2\pi y}{\lambda_i} \right) \quad (4) $$

Where $\lambda_i$ and $amp_i$ are the respective wavelength and amplitude of the $i^{th}$ component.
Evaluation of the reflectance of the pavement surface

The texture profile of the imaged pavement and the locations of the light source and the camera were defined using a 3D cartesian coordinate system (Fig. 2). Then the BRDF variation of the surface due to the direct illumination from the light source can be computed, disregarding the inter-reflection and illumination from other sources such as sunlight. Part of the light from the illuminating source gets reflected from every point on the pavement such as R (x,y,z), scatters due to the diffusivity caused by the slope variance (\( \alpha \)) of the neighborhood of R and reaches different locations of the camera lens. Therefore, BRDF of R (Eqn. 3a) with respect to a number of small elements (\( \Delta A_c \)) that constitute the camera lens area (\( A_c \)) must be evaluated and integrated to determine the average radiance from R with respect to the camera. It has been shown in the Appendix A that the average BRDF at R with respect to the entire camera can be determined as,

\[
\rho(x, y, z)_{avg} = \frac{1}{A_c} \int \int \rho_{id} \frac{1}{\pi \cos \theta_i \cos \theta_r} \exp \left[- \frac{\tan^2 \delta / \alpha^2}{4 \pi \alpha^2} \right] \Delta A_c
\]

(5)

Where, \( \hat{h} \) = Unit vector bisecting the incidence and reflection directions (Fig. 1)

\( \hat{n} \) = Unit vector normal to the surface at R (Fig. 1)

\[
\cos \delta = \hat{h} \cdot \hat{n}, \quad \cos \theta_i = \overrightarrow{LR} \cdot \hat{n} \quad \text{and} \quad \cos \theta_r = \overrightarrow{RP} \cdot \hat{n}
\]

\( \overrightarrow{LR} \) = Unit vector in the direction of incidence (Fig. 2)

\( \overrightarrow{RP} \) = Unit vector in the direction of reflection (Fig. 2)

The appropriate expressions for the above vectors are also derived in the Appendix A.

The BRDF at any point on the surface (i.e. R) with respect to camera aperture segments of 0.5 mm and 30° increments in the radial and angular directions respectively, can be evaluated numerically using Equation (5). The incident light from the source does not reach certain locations on the surface due to occlusion by the surface profile and similarly the reflected light from certain other locations is prevented from reaching the camera.
Both of the above conditions were incorporated when the BRDF for imaged surface was evaluated using Equation (5).

**Conversion of pavement radiance to image intensity**

The image of a pavement feature is formed when the light reflected from that feature (object) enters the camera lens and refracts on to the CCD sensor. A schematic diagram of the optics of image formation is shown in Figure 3. The relationship (Eqn. 6) between the radiance from any surface point (R) and the intensity of its image (ΔE) has been derived in the Appendix B.

\[
\Delta E = \rho h^2 L^* \cos \theta_c A_c \frac{\cos \theta_L}{D^4} \frac{\cos^3 \theta_e}{f^2} \Delta A_c
\]

(6)

Where \( f, \rho, L^*, \) and \( \theta_c \) are the focal length of the lens, BRDF at R with respect to one camera element \( \Delta A_c \), intensity of irradiance immediately below the light source (at Q), and the angle between the normal to the camera aperture and the line RC, respectively. The remaining symbols in Eqn. (6) are illustrated in Fig. 3.

If the light source and the camera are placed at a relatively large height compared to the dimensions of the imaged area, \( \theta_L \) and \( \theta_C \) would not change significantly within one image. Furthermore, since \( h, L^*, A_L \) and \( f \) are constants, Eqn. (6) can be re-written as,

\[
\Delta E = K \rho \cos \theta_c \frac{1}{D^4} \Delta A_c
\]

(7)

Where \( K \) includes the constant quantities in Eqn. (6). Finally, the total intensity \( E \) of the image formed by the surface point R due to light entering the entire lens (of area \( A_c \)) can be determined by combining Eqns. (5) and (7) as:

\[
E = K \frac{\cos \theta_L}{D^4} A_c \rho(x, y, z)_{avg}
\]

(8)
Therefore, Eqns. (5) and (8) can be used to obtain the pixel intensity distribution in the pavement surface image.

**Experimental verification of the image formation model**

The accuracy of the image formation model developed in Section 2.0 was verified experimentally using a single wavelength periodic surface \( n=1, \lambda_i=6\text{mm} \) and \( \text{amp}_i=3\text{mm} \) in Eqn. (4)) molded from clay. The light source was set up above the molded surface with the normal to its surface intersecting the profile at a horizontal distance of 380 mm from it. The camera was placed 500 mm away from the light source and oriented in such a way that the normal lines to the camera aperture and the light source intersected the pavement profile at the same location. Then the surface was imaged at two different camera heights of 305 mm and 610 mm. The actual and simulated images corresponding to the two conditions are shown in Figures 4(a)-(f).

When comparing Figs. 4(a) with 4(b) and Figs. 4(d) with 4(e), it can be observed that the images created by the BRDF model (Eqns. (5) and (8)) resemble those of the actual surface. Furthermore, the images of the same surface mathematically simulated under the same lighting and imaging conditions using the Phong (1975) model programmed in a widely used computer graphics software, *Maya* 7; are also shown in Figs. 4(c) and 4(f). *Maya* is an inbuilt program in a commercial package, which is formulated based on the Phong (1975) reflection model. When the positions of the camera and the light source and the surface profile are input, *Maya* automatically creates the images. Because of *Maya*’s widespread use, in this work it was used to confirm the reliability of the Ward’s model simulations. However the authors’ own coding of the Ward’s model was preferred over *Maya* in the current research because of the former’s flexibility in programming different pavement surfaces, lighting and imaging conditions compared to the latter. In order to quantify the comparison between the images developed based on the Ward’s model and the experimental counterparts (Figure 4), sections of equal sizes were selected from Figure 4(a) and Figure 4(b). Then, the resemblance of the two images was expressed quantitatively by the average difference in intensities between the two images expressed as a percentage of the range of intensities i.e. 256. Since this value was
computed to be only 1.19% per pixel, Ward’s reflection model can be assumed to model closely the experimental images obtained under similar illumination conditions. It is seen that Figs. 4(b) and 4(e) compare reasonably well with Figs. 4(c) and 4(f) as well. The pixel intensities of the synthetic (modeled) image closer to the camera were seen to be higher (Fig. 4(b)) as in the case with its experimental counterpart (Fig. 4(a)). However, Figs. 4(b) and 4(e) show that there is a sharp intensity reduction from the peak of the profile in the modeled images whereas the intensities of the experimental counterparts (Figs. 4(a) and 4(d)) decrease gradually from the peak. This can be attributed to the fact that the exact sinusoidal shape described by Eqn. (4) could not be achieved due to a minor flattening effect produced at the peaks during molding of the clay surface.

**Application of the image model in detection of wear**

In the next phase of the study, the new reflection model was applied to detect the degradation of texture in pavements. For this purpose, a 0.05m x 0.05m segment of a pavement surface was modeled mathematically with the light source and the camera placed on opposite sides of the normal to the center of the surface, 0.05 m apart from each other at heights of 0.5m and 1 m respectively above the modeled surface (Fig. 5(a)). Possible optimum locations of two such imaging systems in a potential field implementation of this technique are shown in Fig. 5(b). As implied in Fig. 5(b) the pavement wear detection can be limited to the wheel path areas where wearing of pavement texture due to traffic is predominant. Using the above setup, the reflection model described in Section 2.2 was used to create the corresponding images of the mathematically represented original and worn profiles, as described later in Section 4.2.

**Tools for assessing pavement wear using digital images**

Several image characteristics can be used for differentiation of digital images of new and worn out pavements and subsequent identification of the extent of degradation of texture and frictional properties. The normalized pixel intensity histogram of a digital image which depicts the statistical distribution of pixel intensities on the gray scale of 0 to 255 provides the simplest tool to compare and contrast images. Khoudeir and Brochard (2004) (Section 1.3) have used specific statistical properties and the autocorrelation
function for this purpose. Alternatively, an appropriately defined brightness function of an image can also be employed as a more reliable measure for comparison of images. However, the perceived brightness of a given intermediate gray-scale intensity between 0 (black) and 255 (white) cannot be defined in a clear-cut manner. To address this issue and define a reliable brightness function, researchers (Cheng et. al., 1999) have considered image brightness as a fuzzy set.

The membership function ($\mu_{\text{bright}}(x)$) of the brightness fuzzy set can be defined in the gray intensity scale of 0 to 255 with three parameters $a$, $b$, and $c$. As illustrated in Fig. 6, the intensities less than $a$ have zero membership and the intensities higher than $c$ have a membership of 1, in the brightness fuzzy set. The degree of brightness for the intensities between $a$ and $c$ would vary gradually from 0 to 1. This variation can be represented using a standard S function described in Eqn. (9) (Cheng et. al., 1999).

$$\mu_{\text{bright}}(x) = \begin{cases} 
0, & x \leq a \\
\frac{(x-a)^2}{(b-a)(c-a)}, & a \leq x \leq b \\
\frac{(x-c)^2}{(c-b)(c-a)}, & b \leq x \leq c \\
1, & x \geq c 
\end{cases}$$

Then the brightness of an image can be expressed as a probability measure as follows:

$$P(\text{bright}) = \sum_{x=0}^{255} \mu_{\text{bright}}(x).p(x)$$

where $p(x)$ is the probability of occurrence of any given intensity $x$ in the evaluated image as displayed in its normalized histogram. The optimum values for parameters $a$, $b$ and $c$ can be found by maximizing the entropy of brightness ($H(\text{bright})$ in Eqn. 11) of a selected standard image.

$$H(\text{bright}) = -P(\text{bright}) \log(P(\text{bright})) - (1 - P(\text{bright})) \log(1 - P(\text{bright}))$$

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In the current investigation a standard gray-scale target (Edmund, 2003) consisting of 17 evenly spaced patches with intensities between 0 and 255 (Fig. 7) was used as the standard image. With \( p(x) \) (Eqn. (10)) determined from the normalized intensity distribution of an image of the standard gray-scale target, the maximization of the brightness entropy function (Eqn. (11)) yielded the optimum \( a, b \) and \( c \) values of 45, 135 and 195, respectively. Then, the brightness evaluation of any other image can be performed using Eqn. (10) with \( p(x) \) obtained from its intensity histogram and \( \mu_{bright}(x) \) evaluated from Eqn. (9) using the optimum \( a, b \) and \( c \) values determined above.

Detection of surface wear based on image brightness

Case 1 – Modeling of single sine wave profiles
The effect of texture wear on the brightness of the original and worn out images was investigated by modeling the images of different texture levels using the reflection model in Equations (5) and (8) under the light source and the camera positions illustrated in Figure 5(a). The brightness of the modeled images of single sine wave surface profiles (Equation 4) with predefined amplitudes (MTD) varying from 1 mm to 5 mm and wavelengths (average texture spacing) varying from 1 mm to 10 mm were determined using Equation (10) and plotted in Figure 8. From Figure 8 it can be observed that for a constant wavelength the image brightness increases with decreasing mean texture depth (MTD) while for a constant MTD, the brightness increases with increasing wavelength. In both cases the increase in brightness can be attributed to the smoothening of the profile. Based on the above preliminary observations it was decided that the consideration of the brightness of pavement images captured under the specific conditions defined in this study (Fig. 5) could be pursued to detect surface wear.

Case 2 – Modeling of complex pavement surface profiles
In the next phase of modeling, two different and more complex profiles were composed of multiple sine waves to closely represent actual texture profiles of relatively rough and relatively smooth pavements. In both profiles the wavelengths were set to be 24, 12, 8, 6 and 4 mm. The wavelength to amplitude ratios \( a_i \) in Equation 12) of the rougher profile were set to be 10, 8, 5, 3 and 2 respectively, while \( a_i \) for the smoother profile was set at a
constant value of 10 for all the wavelengths. Then the above profiles can be expressed mathematically as,

\[
z = \sum_{i=1}^{5} \left( \frac{\lambda_i}{a_i} \right) \sin \left( \frac{2\pi x}{\lambda_i} + \frac{2\pi y}{\lambda_i} \right)
\]

(12)

where

- \( \lambda_i \) is the wavelength of \( i^{th} \) sine curve (\( i = 1, 5 \) mm)
- \( a_i \) is the wavelength(\( \lambda_i \)) to amplitude(\( \text{amp}_i \)) ratio of \( i^{th} \) sinusoidal curve

Three stages of wearing were simulated on the computer by degrading the portion of their profiles above the mean levels by 2%, 4% and 6% of the original profile heights respectively. Figures 9(a) and 9(b) show the smooth and rough profiles respectively, while Figures 9(c) and 9(d) show the different levels of wearing of selected sections of the profiles shown in Figures 9(a) and 9(b) respectively. Figures 10(a) and 10(c) show the respective images of the original profiles shown in Figures 9(a) and 9(b) modeled using Eqns. (5) and (8), while Figures 10(b) and 10(d) show the modeled images of their 6% worn counterparts. The pair-wise comparison of Figure 10(b) with Figure 10(a) and Figure 10(d) with Figure 10(c) shows an increase in image brightness due to wearing.

Fig. 11 is a plot of the brightness Vs the MTD for both pavement surfaces under different stages of wearing. It can be observed from Figure 11 that the images of the smoother surface are significantly brighter than those of the rougher surface at all stages of wearing. Furthermore, Fig. 11 shows the clearly increasing trends of brightness of both profiles as wearing proceeds. The above observations further support the increasing trend of brightness that was observed in Figs. 8 due to smoothening of single sine waves. In summary, the results indicated in Figs. 8-11 demonstrate the viability of setting up an optical imaging system in the manner specified in Fig. 5 to identify the level of macrotexture degradation on a pavement.

**Experimental verification of image brightness variation due to wearing**

In the final phase of the investigation, the theoretical relationship between image brightness and the extent of wear developed in Section 4.2 was experimentally verified using a 460 mm diameter laboratory concrete specimen made to be compatible with the
Circular Track Meter (CTM) (ASTM E 1845-01). The above concrete specimen was grooved at uniformly spaced intervals to obtain the textured surface seen in Fig. 12(a). Then, four 50x50 mm sections evenly spaced out along the CT meter track were earmarked on it as test sections where the experimental results could be averaged to remove any bias due to texture variation. These individual sections were then imaged using the same optical settings used in the theoretical study. Later, the surface of the concrete specimen was gradually worn with sand paper and the worn sections were re-imaged under the same lighting conditions. The CT meter profiles for the original and worn profiles are shown in Figure 13 from which the average MTD can be calculated at each wearing stage as shown in Table 2.

In the preliminary experimental verification reported here, texture was created by grooving the concrete surface to approximately represent a square-waved surface. At each stage of sanding off, it was observed that the edges of the grooves and the surface points with the highest elevations were worn out first. Wearing initiates in actual pavements also at the surface points with the highest elevations. Hence it is expected that the variation of digital image properties during field wearing would follow a trend similar to that achieved in the experiment.

Original and worn images of one of the four selected concrete sections are shown in 12(a) and 12(b) respectively, while Figure 12(c) shows their intensity histograms. Comparison of the two histograms in Figure 12(c) shows that the overall image intensities have increased due to wearing. The computed average brightness values of the images are also shown in Table 2. From the results in Table 2 and the corresponding plot in Figure 14, it can be observed that the brightness of the images of the four sections have increased due to wearing. A similar brightness evaluation was conducted on a field concrete slab at night time using artificial illumination. A selected location of the slab was imaged first and re-imaged on two stages of wearing caused by sand paper. The results are shown in Figures 12(d)-12(f). Additional histograms in Figure 12(g)-12(i) show the increase in the intensities due to gradual wearing shown in Fig 12(d)-(f). Based on the laboratory and
field results it can be concluded that the theoretically predicted increase in image brightness due to wearing is supported by the experimental results.

**Application of image brightness to evaluate pavement friction**

The experimental relationship obtained in Fig. 14 between the image brightness and MTD of a given surface can be calibrated using Equation (13).

\[ B = e^{-k(MTD)^n} \]  

(13)

where \( k \) and \( n \) are assumed to be constants for given pavement and lighting conditions.

For the specific Brightness Vs MTD data set in Fig. 14, one obtains,

\[ B = e^{-2.58(MTD)^{0.203}} \]  

(14)

On the other hand, the Skid Number (SN) (ASTM E 1960-03) of a pavement can be evaluated using as,

\[ SN = SN_o e^{sV/S_p} \]  

(15)

Where, \( s \) and \( V \) are the slip ratio and the speed of measurement. \( SN_o \) is the friction measurement corresponding to static conditions. For the Locked-Wheel Friction Testers (LWST) (ASTM E 274-06) and DFTs (ASTM E 1911-09a), \( s=100\% \). Also, \( S_p \), the speed constant, can be related to the Mean Profile Depth (MPD) as,

\[ S_p = a + b(MPD) \]  

(16a)

Where \( a \) and \( b \) are constants dependent on the method used to evaluate macrotexture. For the CT meter measurements, ASTM E 1960-03 recommended values are \( a=14.2 \) and \( b=89.7 \).

The following relationship recommended by ASTM E 2157 has been used to convert MPDs to MTDs.
\[ MTD = 0.947 \times MPD + 0.069 \] (16b)

The skid-number (SN) of a pavement measured with the LWST or DFT can be related to the brightness of the corresponding images by combining Equations (13), (15) and (16) as follows:

\[
SN = SN_0 e^{-k \times \left( \frac{-\ln B}{k} \right)^{1/n} - 0.069 \times a}
\] (17)

Finally, Equation (17) can be used to calibrate the relationship between the predicted SN at different stages of wearing of a given concrete pavement and the brightness (B) of the corresponding images. As an example, let the LWST measured SN of the initially unworn concrete surface for which the image brightness and MTD variation is defined in Fig. 14 (with k=2.58 and n=0.267), be 42. Then the variation of SN with the brightness of images captured at different stages of wear shown in Table 2 can be evaluated using Eqn. (17). This variation is illustrated in Figure 15 for the standard measurement speed of 65 km/hr.

The above example illustrates the need for calibrating Equation (17) to determine the specific values of SN_0, k and n applicable for a given pavement and a lighting system, prior to field implementation of the developed methodology on that pavement.

**Limitations of the new technique**

A major limitation of the developed technique is its inapplicability on wheel paths where the deposition of tire rubber camouflages the texture, thereby offsetting any increase in brightness in the images due to wear. In addition, the images created using the geometrical and reflection models could differ from the actual images due to camera artifacts and other types of noise. Hence the images collected from survey vehicles have to be pre-processed to remove any noise before they are used to detect the changes in brightness. Another possible limitation could be the complexity of the actual illumination conditions at the time of image capture. This effect can be especially pronounced when images are collected during daytime in the presence of sunlight and inter-reflections from
other sources which are not considered in the modeling. However, this issue can be overcome by imaging during the night time when the imaged pavement surface would be illuminated mostly under the influence of the probe light attached to the evaluation vehicle. In this preliminary analytical investigation and its companion experimental verifications, the image intensity contrasts were predicted based on the surface relief variations only, thus disregarding effects of color variation introduced in the radiant light by different constituent materials. This issue would be critical in the application of this technique to detect wear in asphalt pavements in particular, which constitutes aggregate and binder with contrasting colors. However, this technique can be refined further to incorporate color variations in the BRDF models (Amarasiri et. al, 2010).

Pavement crack evaluation using digital images does not require the detection of features smaller than 1 mm resolution since the widest (hairline) crack considered in pavement rehabilitation is 1 mm in width. Therefore, there has been no imminent need for further advancement in camera resolution to achieve precisions greater than 1 mm. However, the resolution becomes an issue in the advanced texture analysis since higher resolution cameras with resolutions as small as 0.5 mm would be needed to detect the lower end of macrotexture from 0.5 – 1.0 mm.

Finally, the objective of this investigation was to evaluate the wear induced intensity changes in digital images of locations which are deemed to be uncontaminated. As for determining the texture changes at contaminated locations, the intensity differences induced by the contaminants themselves must be accounted for first using verified reflection and refraction properties of the contaminants. Then, the wear induced intensity differences can be evaluated accurately.

**Suggestions for field implementation**

Variations due to (i) illumination and (ii) seasonal effects could also cause changes in the image brightness. Therefore, before evaluating the wear-induced changes, the intensity effects due to illumination must be eliminated using image filtering techniques.
Significant and uniform brightness changes across wheel path and non-wheel-path areas would indicate illumination effects. Filtering techniques are available (Cheng et. al., 1999) to evaluate the average change in intensity across the image and standardize image sets with respect to the intensities.

The effects of seasonal variations and even illumination to some extent can be minimized by limiting the pavement wear induced texture change evaluation to images captured during the same season. Most transportation agencies such as DOTs conduct their network level evaluations on an annual basis. Thus, even network level skid evaluations can be scheduled in such a way that a given pavement can be evaluated every year during the same season. In addition, wear induced brightness changes in images can be magnified by employing more sophisticated cameras that can portray a higher numerical range of intensities than the standard scale of 0 - 255.

Furthermore, as highlighted in the example on the application of this technique, any network-level implementation of this methodology must be accompanied by an initial set of calibration tests for each possible testing scenario associated with different pavement types and illuminations levels. For this purpose, two initial LWST measurements and brightness evaluations of the corresponding images would suffice for any given testing scenario.

**Conclusions**

An image modeling technique was used to explore optical properties of digital images that can quantify the macrotexture and skid resistance changes in pavements. In this regard, a simplified Bidirectional Reflection Distribution Function (BRDF) model with physically meaningful parameters was used to transform the macrotexture of a pavement surface to the corresponding images captured by a digital area-view camera. The modeling results were first verified by matching the theoretically simulated images of a single wavelength 3-D sinusoidal surface with those of a geometrically similar experimentally molded surface. Next the images of a family of 3-D single sine waves with varying amplitudes and wavelengths were modeled to explore specific image
characteristics that would detect surface smoothening caused by changes in the mean texture depth or the texture spacing (wavelength). The above investigation was also extended to include appropriate combinations of 3D sine curves that resemble actual pavement surfaces with different macrotexture levels. Modeling of surface wear consistently revealed monotonic increases in the brightness of the corresponding images captured by a well designed imaging system placed at an optimum location relative to the pavement.

Modeling results were verified experimentally by first using a laboratory concrete specimen compatible in size with the Circular Track Meter (CTM) and worn out in stages using sandpaper. The investigation was later extended to a field concrete slab as well. Processing of the images of the original and worn concrete surfaces confirmed the definitive increase in image brightness due to wearing. It was demonstrated that once the brightness variation trend of the images corresponding to initial stages of wearing of a given pavement is established, the model can be calibrated to determine the extent of pavement wear at any future stage based on evaluating the brightness of the relevant images. In addition, the conventional correlation between the skid number and MTD of a pavement was employed to illustrate how the new technique can be extended to predict the degradation of skid resistance, based on evaluating the brightness of pavement images.

It is known that the use of devices such as Locked-wheel skid testers is impractical for periodic network level screening of highway pavements for skid resistance deficiencies. On the other hand, with further refinement of the technique introduced in this study, if the evaluated brightness of pavement images routinely collected by various transportation agencies can be used to predict the degradation of skid-resistance of pavements, it would provide a valuable tool for network-level screening. Since this texture modeling approach can even reach the microtexture of pavements, it could provide a valuable tool to investigate the types of information on pavement microtexture that could also be revealed on further enhancement of camera resolution.
Acknowledgment
The National Aeronautics and Space Administration (NASA) grant NNL06AA17A is gratefully acknowledged.

References


Edmund Industrial Optics (2003), Large Garscale target,


**APPENDIX A**

**Derivation of BRDF for a surface profile with respect to an aerial-view camera.**

From Fig. 2, the incident light vector at R can be determined as

\[
\overrightarrow{LR} = -x_i - y_j + (h - z)k = D\overrightarrow{LR}_{\vec{u}} \tag{A1}
\]

where \(D\) is the distance LR and \(\overrightarrow{LR}_{\vec{u}}\) is the unit vector. In order to compute the irradiance (incident light) on the camera, a transformation can be used to convert the
aperture from a 3D plane circle in the \((x,y,z)\) system to a 2D circle in the \((x',y',z')\) system as shown in Figure A.

If \(z'\) is normal to the aperture of the lens, then the camera plane can be identified by the unit vector \(\vec{k}\) along \(z'\) defined by two of its directional cosines \(l\) and \(m\) as;

\[
\vec{k} = l\hat{i} + m\hat{j} - \sqrt{1-l^2-m^2}\hat{k}
\]  \hspace{1cm} (A2)

Then the unit vector \(\hat{i}\) can be selected such that \(x'\) axis lies on the \(xy\) plane that intersects the circle. Since \(\hat{i}\) and \(\hat{k}\) are perpendicular to each other (i.e. \(\hat{i}\hat{k} = 0\)), the transformed \(\hat{i}\) can be expressed using the original \(\hat{i}\) and \(\hat{j}\) as

\[
\hat{i} = \frac{m}{\sqrt{l^2 + m^2}}\hat{i} - \frac{l}{\sqrt{l^2 + m^2}}\hat{j}
\]  \hspace{1cm} (A3)

FIGURE A Polar and Cartesian Coordinate Systems for the Camera Aperture

Also since the third unit vector \(\hat{j}\) is perpendicular to both \(\hat{i}\) and \(\hat{k}\) (i.e. \(\hat{j} = \hat{k} \times \hat{i}\)), the transformed \(\hat{j}\) can be expressed using the original \(\hat{i}\), \(\hat{j}\) and \(\hat{k}\) as

\[
\hat{j} = -\frac{l\sqrt{1-l^2-m^2}}{\sqrt{l^2 + m^2}}\hat{i} - \frac{m\sqrt{1-l^2-m^2}}{\sqrt{l^2 + m^2}}\hat{j} - \left(\frac{l^2}{\sqrt{l^2 + m^2}} + \frac{m^2}{\sqrt{l^2 + m^2}}\right)\hat{k}
\]  \hspace{1cm} (A4)
Using the transformation defined by Eqns (A2)-(A4), the vector $\mathbf{CP}$ (Figure A) can be represented in the $(x,y,z)$ coordinates as,

$$
\mathbf{CP} = \left( \frac{mr\cos\phi - r\sin\phi\sqrt{1-l^2-m^2}}{\sqrt{l^2+m^2}}, \frac{l\cos\phi + rs\sin\phi\sqrt{1-l^2-m^2}}{\sqrt{l^2+m^2}}, -r\sin\phi\sqrt{l^2+m^2} \right) \mathbf{k}
$$

(A5)

Let the vector joining R and the center of the camera C (Figure A) be,

$$
\mathbf{RC} = C_x\mathbf{i} + C_y\mathbf{j} + C_z\mathbf{k}
$$

(A6)

Since,

$$
\mathbf{RP} = \mathbf{RC} + \mathbf{CP}
$$

The reflected light from R to P can be represented by the following vector

$$
\mathbf{RP} = \left( C_x + \frac{mr\cos\phi - r\sin\phi\sqrt{1-l^2-m^2}}{\sqrt{l^2+m^2}} \right) \mathbf{i} + \left( C_y - \frac{l\cos\phi + rs\sin\phi\sqrt{1-l^2-m^2}}{\sqrt{l^2+m^2}} \right) \mathbf{j} + \left( C_z - r\sin\phi\sqrt{l^2+m^2} \right) \mathbf{k}
$$

$$
= D \mathbf{RP}_u
$$

(A7)

where $D$ is the distance RP and $\mathbf{RP}_u$ is the unit vector. Then using the unit vectors in the $\mathbf{RP}$ and $\mathbf{LR}$ directions, the half vector between the incident and the reflected light (Figure 1) is defined by,

$$
\mathbf{h} = \mathbf{RP}_u + \mathbf{LR}_u = \mathbf{h} |\mathbf{h}|
$$

(A8)

If the unit normal to the pavement texture profile at point $R(x,y,z)$ is specified using two known directional cosines $N_x$ and $N_y$ as follows,

$$
\mathbf{n} = N_x\mathbf{i} + N_y\mathbf{j} + \sqrt{1-N_x^2-N_y^2}\mathbf{k}
$$

(A9)

Then, the angular parameters required for Ward’s BRDF expression (Eqn. (3)) to be applied at the surface location R can be determined as,

$$
\cos\delta = \mathbf{h} \cdot \mathbf{n}
$$

(A10)

$$
\cos\theta_i = \mathbf{LR}_u \cdot \mathbf{n}
$$

(A11)

$$
\cos\theta_r = \mathbf{RP}_u \cdot \mathbf{n}
$$

(A12)
Finally, by applying Eqn. (3a) to an element of area \( \Delta A_C \) of the aperture, the average BRDF at R with respect to the entire camera can be determined as,

\[
\rho(x, y, z)_{avg} = \left[ \frac{1}{A_C} \int_0^{\pi} \int_0^{\pi} \rho_d \frac{1}{\cos \theta_i \cos \theta_r} \exp\left[ -\frac{\tan^2 \delta}{4\pi\alpha^2} \right] \Delta A_C \right] \]

(A13)

Where \( \Delta A_c = r(\frac{dr}{d\varphi}) \) (Fig. A) and \( A_c \) is the area of the camera aperture.

APPENDIX B

Relationship between the photo intensities of objects and their images

In Fig. 3, \( \delta O \) is the area of the neighborhood of R from which light is reflected to the corresponding area \( \delta I \) of the image. The flux leaving the pavement surface area \( \delta O \) toward the camera is given by

\[
F = L_R \delta O \delta \Omega \]

(B1)

where \( L_R \) is the radiance at \( \delta O \). The solid angle subtended by \( \Delta A_c \) on R can be expressed as,

\[
\delta \Omega = \Delta A_c \frac{\cos \theta_r}{D_c^2} \]

(B2)

If no loss of photo energy is assumed within the camera, and the intensity caused by the light refracted within the element \( \Delta A_c \) at the image area \( \delta I \) is \( \Delta E \), then

\[
F = \Delta E \delta I \]

(B3)

Substituting from Eqn. (B3) in Eqn. (B1),

\[
\Delta E \delta I = L_R \delta O \delta \Omega \]

(B4)

Using Eqn. (B2), Eqn. (B4) can be rewritten as

\[
\Delta E \delta I = L_R (\delta O) \Delta A_c \frac{\cos \theta_r}{D_c^2} \]

Or
\[ \Delta E = L_R \frac{\partial O}{\partial I} \Delta A_c \cos \theta_r \frac{1}{D_c^2} \]  
(B5)

From basic optics it follows that the light originating from an object \( O \) and passing through the center of the camera lens (C) continues without refraction to form its image \( I \). Hence the solid angles subtended at the camera center C by \( O \) and \( I \) are equal and opposite. Then, by evaluating each solid angle one obtains,

\[ \frac{(\partial O) \cos \theta_r}{D_c^2} = \frac{(\partial I) \cos \theta_c}{(f / \cos \theta_C)^2} \]

Or

\[ \frac{\partial O}{\partial I} = \frac{\cos^3 \theta_c D_c^2}{f^2 \cos \theta_r^i} \]  
(B6)

Where \( \theta_c \) is the angle between the normal to the aperture at C and the line CR (Figure 3) and \( \theta_r^i \) is the angle between the normal to the modeled surface and CR. Since the camera lens is relatively small in area, it can be assumed that \( \theta_c = \theta_r \) and \( D_c = D_c \). Therefore, by substituting in Eqn. (B5) from Eqn. (B6)

\[ \Delta E = L_R \cdot \frac{\cos^3 \theta_c \Delta A_c}{f^2} \]  
(B7)

From Equation (1a) the reflected radiance \( L_R \) and the incident radiance \( L' \) can be related by,

\[ L_R = \rho L' \cos \theta_i \Delta \omega \]  
(B8)

Where \( \Delta \omega = A_L \cdot \frac{\cos \theta_L}{D^2} \) and \( \theta_L \) is the inclination of the face of the light source to the plane normal to RL

Furthermore, since the attenuation of radiance is inversely proportional to the square of the distance,
\[ L' = \left( \frac{h^2}{D^2} \right) L^* \] (B9)

Where \( L^* \) is the radiance on the surface immediately below the light source \( Q \). By combining Eqns. (B7), (B8) and (B9) one obtains,

\[ \Delta E = \rho h^2 L^* \cos \theta_i A_L \cdot \frac{\cos \theta_i}{D^4} \cdot \frac{\cos^3 \theta_e}{f^2} \cdot \Delta A_c \] (B10)
# TABLE 1 Classification of Texture based on Wavelengths (ISO, 1997)

<table>
<thead>
<tr>
<th>Type</th>
<th>Wavelength (mm)</th>
<th>Description of texture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Micro-texture</td>
<td>λ&lt;0.5</td>
<td>Formed by either fine aggregate particles (sand) or surface roughness of the large aggregate</td>
</tr>
<tr>
<td>Macro-texture</td>
<td>0.5&lt;λ&lt;50</td>
<td>Same order of size as coarse aggregate or tire tread elements</td>
</tr>
<tr>
<td>Mega-texture</td>
<td>50&lt;λ&lt;500</td>
<td>Same order of size as tire/road contact area</td>
</tr>
<tr>
<td>Unevenness</td>
<td>500&lt;λ</td>
<td>Surface roughness that affects the ride comfort</td>
</tr>
</tbody>
</table>

# TABLE 2 Brightness Variation due to Wearing

<table>
<thead>
<tr>
<th>Surface Description</th>
<th>Mean Texture Depth (MTD) – mm</th>
<th>Brightness of Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Originally grooved</td>
<td>0.253</td>
<td>0.1702</td>
</tr>
<tr>
<td>After wearing stage 1</td>
<td>0.207</td>
<td>0.1821</td>
</tr>
<tr>
<td>After wearing stage 2</td>
<td>0.198</td>
<td>0.1834</td>
</tr>
<tr>
<td>After wearing stage 3</td>
<td>0.187</td>
<td>0.1894</td>
</tr>
<tr>
<td>Smooth surface</td>
<td>0.172</td>
<td>0.2053</td>
</tr>
</tbody>
</table>
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FIGURE 1 Illustration for Ward’s Reflection Model
FIGURE 2 Illustration of the Imaging System Setup

Light Source
L (0,0,h)

Lens aperture

C(cx,cy,cz)

Normal to the Aperture

\[ l_z + m_j - \sqrt{1 - i^2 - m^2 \ k} \]

\[ \Delta A_C \]

Origin of Coordinates
O (0,0,0)

Observed Point
R(x,y,z)

FIGURE 2 Illustration of the Imaging System Setup
FIGURE 3 Illustration of the Image Formation Process
FIGURE 4(a) Actual Image of the profile taken at 305 mm above the surface

FIGURE 4(b) Modeled (Ward) Image of the simulated profile corresponding to Fig. 4(a)

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Brightness = \( e^{-2.58(MPD)^{0.267}} \)

wearing
Figure 15 Variation of Skid Number with Brightness