Texture Measurement and Friction Estimation Using Laser Data Acquisition and Neural Networks

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Abstract: - This paper discusses the development of a neural net model for predicting Skid Number, a statistical index related to the texture characteristics of pavements. The model is based on surface roughness characteristics of pavements as measured by a laser based measurement system.

Key-Words: - Texture Measurement, Friction, Skid Number, Laser, Neural Networks.

1 Introduction

This paper discusses a laser based texture measurement system and the use of neural networks in the analysis of the data to predict the skid number (friction) of the tire/pavement system.

The skid resistance, measured as the skid number, or frictional properties, of a pavement surface in contact with a given tire under similar conditions has been shown to be largely determined by the texture of the surface [1, 2]. Texture is comprised of two components: macrotexture and microtexture.

Macrotexture is the deviations of a pavement surface from a true planar surface with the characteristic dimensions of wavelength and amplitude from 0.5 mm (0.02 in.) up to those that no longer affect tire-pavement interaction [3]. It is generally believed that macrotexture provides the drainage on wet pavement and determines the rate that skid resistance decreases with increasing speed.

As discussed in [2] the Skid Number (SN) is related to the coefficient of friction, μ, by

$$SN = 100\mu = 100(F/W)$$

The research used raw laser measurements made during skid measurements so that the exact wheel path was followed by the skid trailer used for obtaining the skid numbers. The skid numbers and laser data was taken from measurements made during a research project from 1998-2000. For this data, a neural network was used in the analysis of the data. First the data was pre-processed by computing a statistic referred to as a 'string number statistic', and this string data was then fed into a neural network to estimate the skid number. The training set comprised the string values and the associated skid number measurements. The neural network was used to predict the skid number based on other profile data pre-processed by computing the sting number.

2 Measurement Hardware

This section presents a description of the laser system used for texture measurement. The measurement system used is shown in Figure 1. As indicated in this figure, the system consisted of a high resolution laser along with inputs from a distance sensor to indicate vehicle position as the vehicle moves along the pavement. The raw digital laser readings are sent directly to a PC via a special interface board or PC Laser Interface Module (PCLIM).

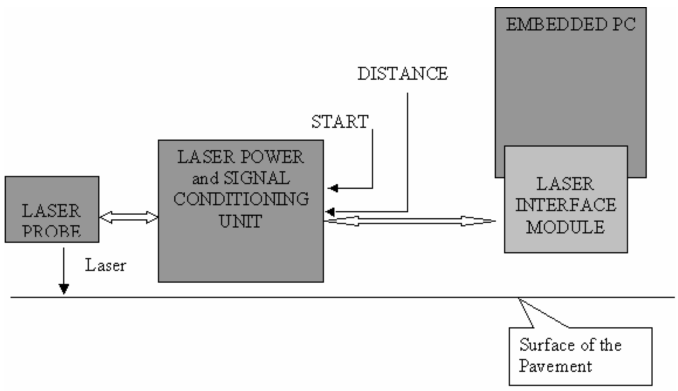

Figure 1: Schematics of Texture Measurement system.

The laser used was a 77 kHz texture laser, developed by Selcom for such measurements. The PCLIM was built at the University of Texas at Arlington and provided a means for buffering and averaging the raw texture displacement readings and transferring these readings to a PC. At the time the system was used, Selcom systems used averaging boards discarding readings that were detected as bad from the laser probe. Bad readings were typically cases when the laser return signal was not received during measurements. For this case, it would be discarded and replaced by the next reading (assuming it was good). If readings are discarded, then the number of time-readings between two consecutive distance-readings could vary for the same speed, thus making it difficult to obtain accurate longitudinal wavelength information. The PCLIM board was designed to let the software determine how to average the laser readings, as well as maintaining wavelength integrity. The PCLIM (Figure 2) provided a way to read the laser values directly into memory via a PC104 data bus. The next section provides details on the architecture of a Laser Power and Signal Interface Unit. Figure 3 shows the laser components and figure 3 shows the laser installed on the skid trailer used in the data acquisition.

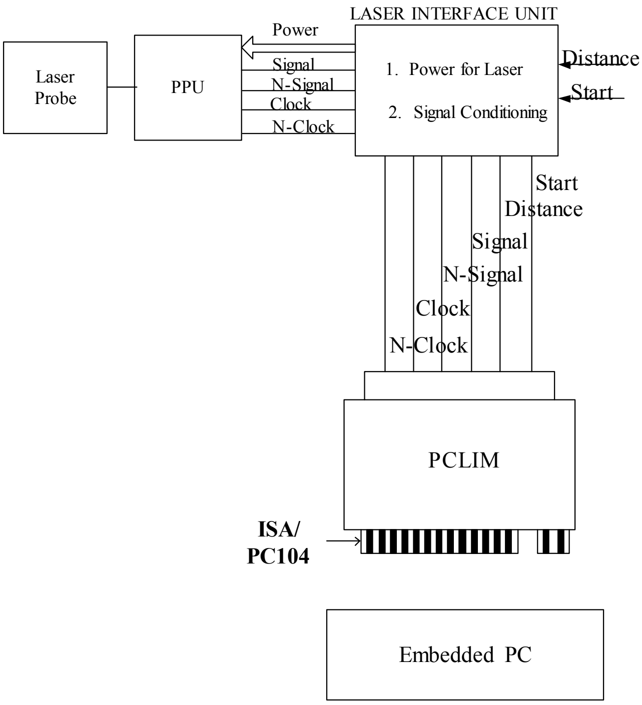

Figure 2: PCLIM Configuration

3 Data Analysis

To investigate whether the skid number could be predicted from the profile data, a neural network was used after the data was pre-processed. This section discusses the pre-processing of the data and the use of the neural network.

Figure 3 Installation of the texture laser on test trailer during data acquisition.

3.1 Data format and Pre-processing.

The tests were made at several test sites in Texas. The raw test data was stored in files of the format shown in figure 8. Files were stored in the format MMDDHHmm.SS where MM is the month, DD is the day, HH is the hour, mm is the minute, and .SS is the second. For example 08031433.19 was collected on August 3rd at 14:33:19. These files contained the raw profile data read by the laser along with header information. Two sets of data were collected in February and in June, and will be referred to hereafter as "'02" and "06" data. The header information includes various parameters governing the laser setup and other information. The typical file format is illustrated in Figure 4. Figure 5 illustrates the wavelength and amplitude components of the texture profile

A statistic frequently used in describing texture is mean profile depth or MPD. The computation of this statistic has been well defined both by the ASTM and the ISO. The profile is given in terms of amplitude and distance.

For the short texture wavelength range of surface texture the longer wavelengths affected by vehicle or trailer influence is filtered out.

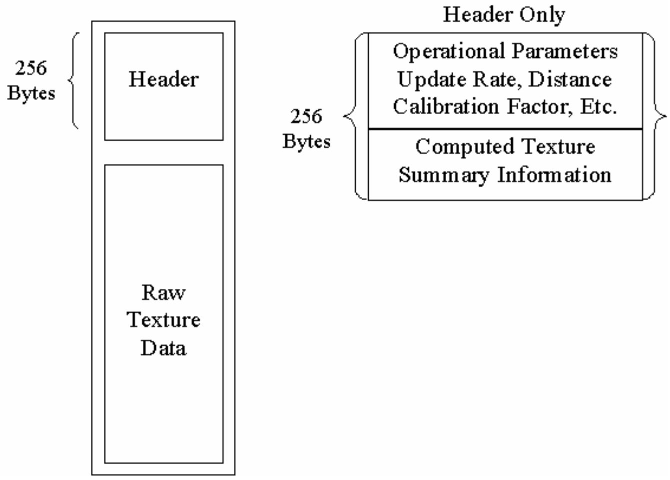

Figure 4: Data file format.

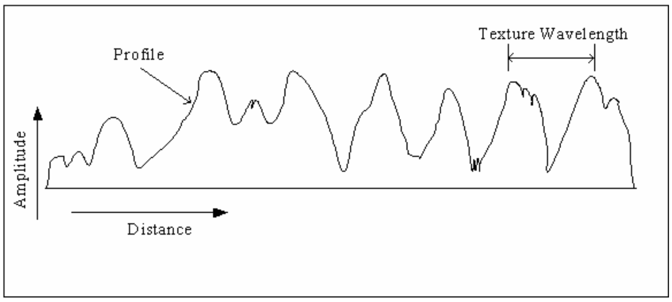

Figure 5: Texture Profile Amplitude and Wavelength.

Figure 6 shows the Mean Profile Depth statistic. This statistic is simply the average value of the profile depth over a specified distance (window or referred to as the baseline). Estimated Texture Depth (ETD) is used to estimate mean texture depth and is defined by the equation:

ETD = 0.2 + 0.8 * MPD.

The baseline is typically 100 mm or 3.94 inches (related to the diameter of the spreader tool used in the volumetric method

After the profile data was read in from the tests, investigations to see if the skid number could be predicted using this profile data were conducted. The data was first pre-processed using various statistics such as MPD, texture variance, etc., and attempts made to correlate these statistics to the skid number of the section measured. One of the statistics used tried was a variation of the string line rut measuring statistic. The string method is applied as illustrated in Figure 67 The string method requires two parameters, a base length or BL, and string length, SL. Similar to the European String Method used for rut measurements, an imaginary string is stretched across a set of points, P1 to P16 as indicated in Figure 7. The set of points between SL are replaced with a new set, where all points making contact with the string have a zero value and those that fall below the string are replaced with the difference between the point and the imaginary string. The new set of 'string filtered' points are then further divided into one or more subsets, where the length of the subset is BL. In Figure 11, the set of filtered SL points consists of 3 subsets, BL1, BL2, and BL3.

A second variation of the method consists of including in each subset BLi, only those points that do not make contact with the string. Although not necessary for use with each statistic, one or more of the above statistics can be computed for each BL subset and an average of the statistics for the SL set determined. For example, using the RMS statistic (also referred to as STD) and using the second variation we get for the first two subsets.

$$STD_1 = \frac{\left[\sum_{i=1}^{3} a_i^2 - \frac{\left(\sum_{i=1}^{3} a_i \right)^2}{\sqrt{2}} \right]^{1/2}}{\sqrt{2}}$$

$$STD_2 = \frac{\left[\sum_{i=4}^{7} a_i^2 - \frac{\left(\sum_{i=4}^{7} a_1 \right)^2}{4} \right]}{\sqrt{3}}$$

With Base Length BL, and String Length SL defined as

$$SL = (P_1, P_2, P_3, \ldots\ldots P_{14}, P_{15})$$

$BL_1 = (P_1, P_2, P_3, P_4, P_5, P_6)$

$BL_2 = (P_4, P_5, P_6, P_7)$, etc.

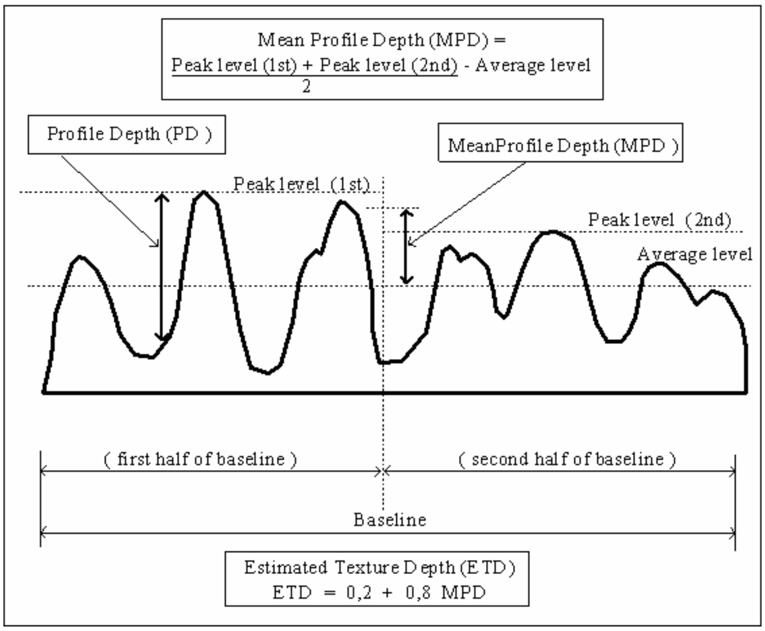

Figure 6: Texture profile and related definitions

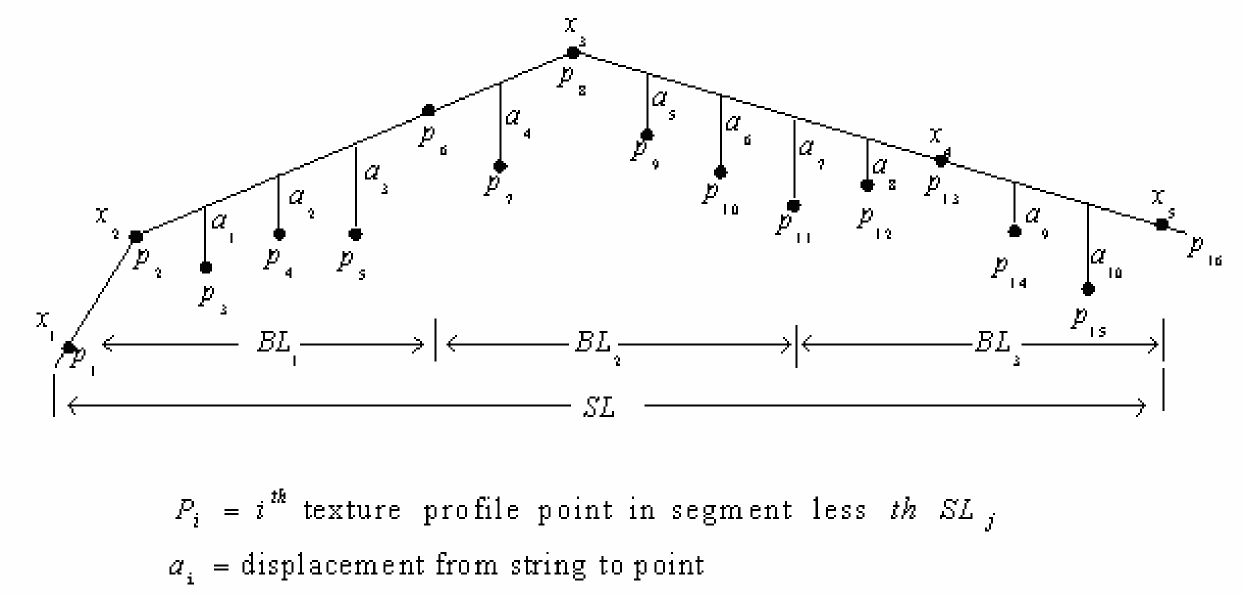

Figure 7: Definition of string parameters.

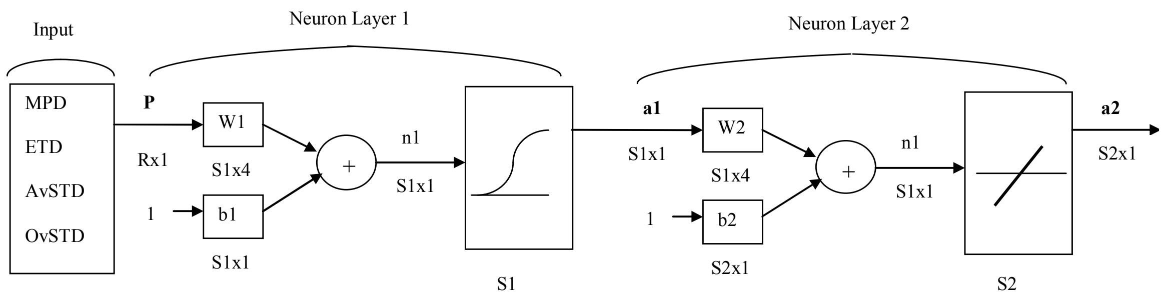

Figure 8: Neural Network Schematics

3.2 Neural Network SN Prediction

A 2-layer log-sigmoid and pure-linear back-propagation neural network with biased terms was developed using MatLab was developed to predict the skid number from the profile data process with string routines discussed above. A training set of 100 points randomly selected form the '02 and '06 data gathered was created. The file includes values for MPD, ETD, and the STDs computed using the string filter described above and an associated skid number for the section of data stored in the file. Two test data sets were formed from the remaining '02 and '06 data. Figure 12 shows a schematic of the Neural Network.

To test the prediction ability of the neural network, test sets of data comprising approximately 200 MPD, ETD, and deviations using string numbers for a given skid test was input into the network. Associated with each test set was known skid numbers, but these skid numbers were not input into the test sets but were used to evaluate the predicted skid number produced by the neural network. The network predicts the skid number based on the associated string values. Figure 13 shows the predicted verses measured skid number for a set of data. Typically, the predicted values correlated to about 75 percent of the actually measured skid numbers. Clearly, using this technique one can predict the skid number given the profile data.

To determine the validity of the prediction, standard regression statistics were run on the predicted and measured skid number. Typical R-squared values were from 0.73 to 0.78. Table 1 lists the runs of the data collected over a 3 month period.

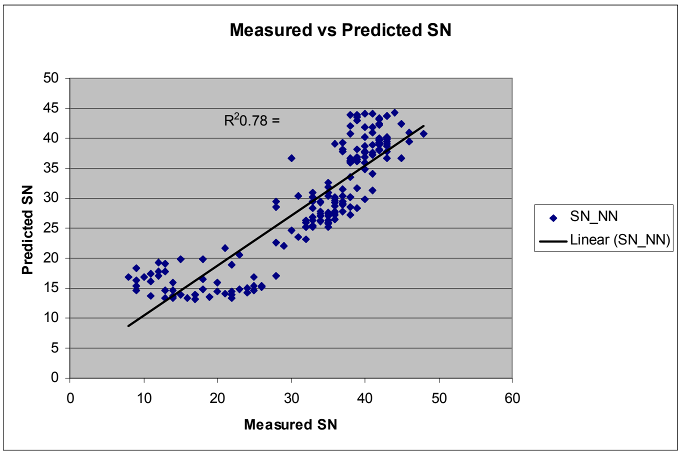

Figure 13: Correlation between neural network predicted SN and measured SN for the '02 data. Similar results were obtained for the '06 data.

Regression Statistics	
'02 data R Square	0.78
Observations	200
'06 data R Square	0.73
Observations	212

Table 1: Regression statistics for the best run.

4 Conclusion

This paper presents a hardware and software set of systems to measure the texture of pavement and to accurately predict the skid number of the pavement given the profile data. Although these developments are specific to the skid number of pavement, which is directly related to the friction between the pavement and the tire, it may be possible to adapt these techniques to the measurement of friction in other situations.

References:

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