Exploring Pavement Texture and Surface Friction Using Soft Computing Techniques

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Background

- Pavement friction: the force resisting the relative motion between vehicle tire and pavement surface (contact method)
  - Static devices: British pendulum tester (BPT), dynamic friction tester (DFT)
  - High speed instruments: locked wheel skid trailer, grip tester - consuming water & tire with limited contact area
  - Depending on many factors, such as testing speed, temperature, water film, tire tread, traffic wander
**Background**

- Pavement texture: the deviations of pavement surface from a true planar surface (Non-contact method)
  - Macrotexture: sand patch, CTM, high speed profiler; widely used indicators - MPD (2D) and MTD (3D)
  - Microtexture: primarily in laboratory (<0.5 mm)
  - Could be a surrogate of friction with more versatile applications through various vehicle-pavement simulations
Problem Statement

- No consistent relationships between texture indicators and friction via traditional methodologies
  - MPD & MTD of macro-texture: very simplified representation of texture profiles, which could result in the lose of useful information from rich data
  - Micro-texture: limited in laboratory, high speed instrument not available
Preliminary Result

(a) Apparent Friction and MPD Improvement (Site A: IA-I380)

(b) Apparent Friction Improvement but M MPD (Site B: OK-SH20)
Preliminary Result

Conventional pavement texture indicator MPD: inadequate to predict pavement friction number consistently for diversified pavement surfaces
Potential Solutions

- Novel texture parameters, besides MPD & MTD, which correlate better with friction
  - From other disciplines, such as mechanical engineering, tire industries, et al.
  - Use both macro- and micro-texture indicators, combining with field and laboratory (based on surface topography) data sets

- Better use of macro-texture profile data
  - Extract information from profiles using advanced soft computing technologies
  - Directly use rich profile data as a whole for friction estimation
Available Instrument Resources

- Grip tester: continuous friction measurements
- Dynamic friction tester: portable device to measure the speed dependency of pavement friction
- AMES high speed profiler: MPD (macro-texture)
- LS-40 surface scanner: 0.01 mm resolution (macro- & micro-texture)
Available Instrument Resources

- **Grip Tester**
  - Continuously measure longitudinal friction
  - Operating around the critical slip of an anti-lock braking system
  - Much shorter testing section length requirement
  - Airports and highways safety management
Available Instrument Resources

- Dynamic Friction Tester (DFT)
  - Portable device to measure the speed dependency of pavement friction
  - Acquiring friction at testing speed from 10 to 80 km/h
Available Instrument Resources

- AMES 8300 High Speed Profiler
  - Surface macro-texture data & standard profile data at highway speeds
  - Mean Profile Depth (MPD)
  - International Roughness Index (IRI)
Available Instrument Resources

- LS-40 Surface Analyzer
  - Data Pixel: 2048 x 2448
  - Resolution: 0.01mm (0.0004”)
  - Pavement surface micro- & macro-texture
Wavelet based Analysis

- To decompose pavement macro-texture data into multi-scale characteristics
- To investigate the suitability of wavelet based indicators for pavement friction prediction
- AMES data vs. grip tester data

Novel Texture Parameters

- Five categories: height, volume, hybrid, spatial, and feature based parameters from various disciplines (24 indicators in total)
- To examine the relationship between them and friction
- LS-40 data vs. DFT data
Wavelet analysis based evaluation of texture contribution to friction at macro- and micro-texture levels

- Butterworth filter: decompose high resolution texture profile data into macro- and micro-level
- Wavelet transformation: calculate wavelet energy as texture indicator at macro- and micro-levels
- Determine the dependency of pavement friction on macro- and micro-texture at different speeds
- Investigate multi-scale texture within the critical depth of pavement
Deep Learning (DL) based friction prediction model using pavement texture data

- Investigate the suitability of DL architectures for friction prediction model
- Develop Convolutional Neural Network (CNN), one of the most widely used DL methodologies, for training, validation, and testing
- Evaluate the accuracy and performance of the developed CNN model
Methodology

- **Wavelet based Analysis**
  - Separate pavement macro- & micro-texture via Butterworth filter
  - Investigate the suitability of wavelet based indicators for pavement friction prediction
  - LS-40 data vs. DFT data

- **DL based Analysis**
  - FrictionNet: CNN based model for training, validation, and testing
  - Predict friction with texture data
  - AMES data vs. grip tester data
Part I
Wavelet based Analysis
Data Source

OKLAHOMA DOT SPR 2115, LONG TERM PAVEMENT PERFORMANCE MONITORING OF SIX LTPP SPS-10 SECTIONS IN OKLAHOMA WITH 3D LASER IMAGING
Wavelet Analysis

Step 1: De-noise Image

Clean 3D Image

Step 2: Apply Butterworth Filter

Macro- & Micro-texture

Step 3: Perform Wavelet Analysis

Total Energy Matrix

Step 4: Conduct Correlation Analysis

Critical Depth of Pavement

Step 5: Develop Friction Prediction Model
Wavelet Analysis

- Site 2 – Macro-texture
- Site 6 - Macro-texture
- Site 2 – Micro-texture
- Site 6 - Micro-texture

Butterworth Filter
Wavelet Analysis

- Decompose macro- & micro-texture into combination of different wavelets
  - Energy
    \[ E_{ni} = \frac{1}{N} \sum_{j,k} (D_{ni}(b_j, b_k))^2 \]
  - Total Energy (TE)
    \[ TE = \sum_{n=1}^{d} E_{ni} \]
Critical Depth of Texture

- Topmost asphalt layer: direct contact with tire that actually contribute to friction
  - Mean tire penetration depth (Kennedy et al. 2015): 0.03 mm (passenger car) vs. 0.08 mm (truck)

- Critical depth of texture
  - Cut 3D surface into slices with various depths, while using the top portion to relate to friction
  - Correlation analysis between $T_{Emacro}$ & $T_{Emicro}$ with friction at different DFT speeds: to determine the critical depths at both texture levels
Critical Depth of Texture

Site 2 – Full range

Site 2 – Top 1.4 mm

Site 6 – Full range

Site 6 - Top 1.4 mm

Top topography analysis of a fractal surface
Critical Depth of Texture

- **Macro-texture:** 1.4 mm of critical depth
- **Micro-texture:** 0.5 mm of critical depth
Friction Prediction Model

- 72 testing points on LTPP SPS-10: 75% for model development, 25% for validation
- Relate friction to $T_{E_{\text{macro}}}$ & $T_{E_{\text{micro}}}$ at the critical depth of texture
- Evaluate macro- and micro-texture contributions to DFT friction at different speeds
- Include ambient temperature ($T$) in the model

$$Friction \ Number = a + \sum_{1}^{2} T E_i \ast b_i + T \ast c$$
Friction Prediction Model

Validation Result at 10km/h

$R^2 = 0.57553$

$SSE = 0.062487$
Friction Prediction Model

Validation Result at 60km/h

$R^2 = 0.75259$

SSE = 0.0057087
Part II
Deep Learning based Analysis
Data Source

FHWA, LONG TERM PERFORMANCE MONITORING OF HIGH FRICTION SURFACING TREATMENTS (HFST) SITES (3 YR)
Data Source

FHWA, LONG TERM PERFORMANCE MONITORING OF HIGH FRICTION SURFACING TREATMENTS (HFST) SITES (3 YR)
Deep Learning

- “a new area of Machine Learning research, which has been introduced with the objective of moving closer to one of its original goals: Artificial Intelligence”
Profile Spectrogram

- Pair raw pavement texture profile with friction number for each 3-feet segment
- Spectrogram: a visual representation of the spectrum of signal frequencies as they vary with time or some other variable
Convolutional Neural Network (CNN)

- FrictionNet architecture
  - 6 layers: 2 convolution, 3 fully connected, and 1 output layer
### CNN Architecture

- **Input:** Spectrogram of texture profile
- **Output:** Friction levels from 0.2 to 1.0 in 0.1 interval
- **Tuned hyper-parameters:** 606,409

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<th>Layer</th>
<th># Parameters</th>
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<tr>
<td>Layer 1: Convolution</td>
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<td>Layer 2: Convolution</td>
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<td>Layer 3: Fully Connected</td>
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<td>Layer 5: Fully Connected</td>
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<td>Layer 6: Output</td>
<td>297</td>
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<tr>
<td><strong>Total</strong></td>
<td><strong>606,409</strong></td>
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Training

- 63,000 pairs of data: randomly select 80%, 10% and 10% data for training, validation, and testing
- Training platform: MXNet
- Training hardware: NVIDIA GeForce GTX TITAN Black
- Training time: 1.68 h
Training Techniques

- Learning method: Stochastic Gradient Descent
- Initialization of parameters: Xavier
- L2 regularization and Dropout: combat overfitting
- Cost function: cross-entropy

\[ CE(label, output) = - \sum_i label_i \log(output_i) \]
Training Techniques

- Softmax function: probability distribution of predicted friction number

\[
\text{softmax}(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}
\]

- Accuracy: evaluate the goodness of CNN model

\[
\text{accuracy}(y, \hat{y}) = \frac{1}{n} \sum_{i=0}^{n-1} 1(\hat{y}_i == y_i)
\]
Accuracy Summary

- Training accuracy: 99.99%
- Validation accuracy: 90.13%
- Testing accuracy: 90.63%
Conclusions

- Top 1.4 mm of pavement texture: critical portion in the context of tire-road contact
- Macro-texture: primarily contributions to friction at high speed
- Micro-texture: governs friction at low speed
- Ambient temperature: significant factor for friction performance
Conclusions

- Large amount of texture and friction data collected on diverse pavement surfaces
  - 50,400 pairs of data for training, 12,600 pairs of data for validation and testing

- FrictionNet: CNN based DL friction prediction model using pavement texture data
  - Six layers with more than 600,000 parameters
  - Achieve 99.99% training and 90.63% testing accuracy
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Questions?

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