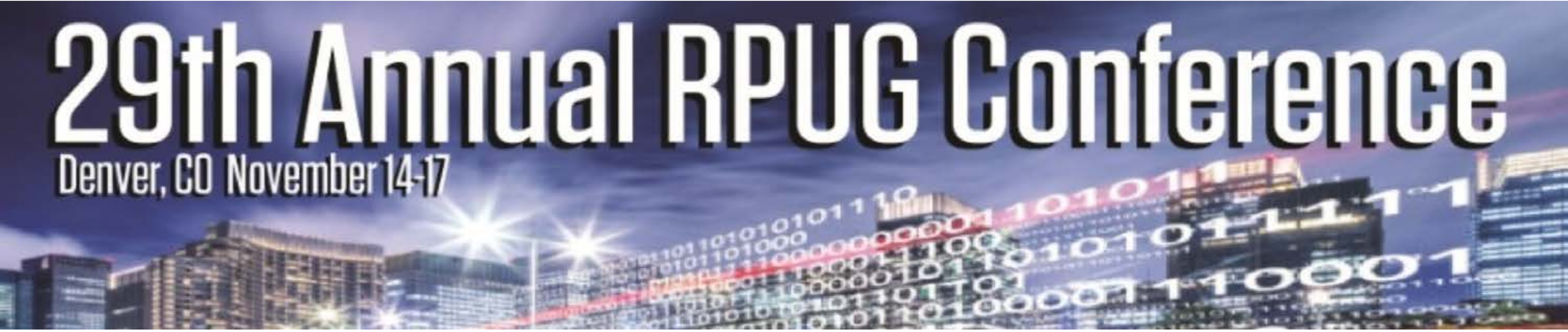

Exploring Pavement Texture and Surface Friction Using Soft Computing Techniques

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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

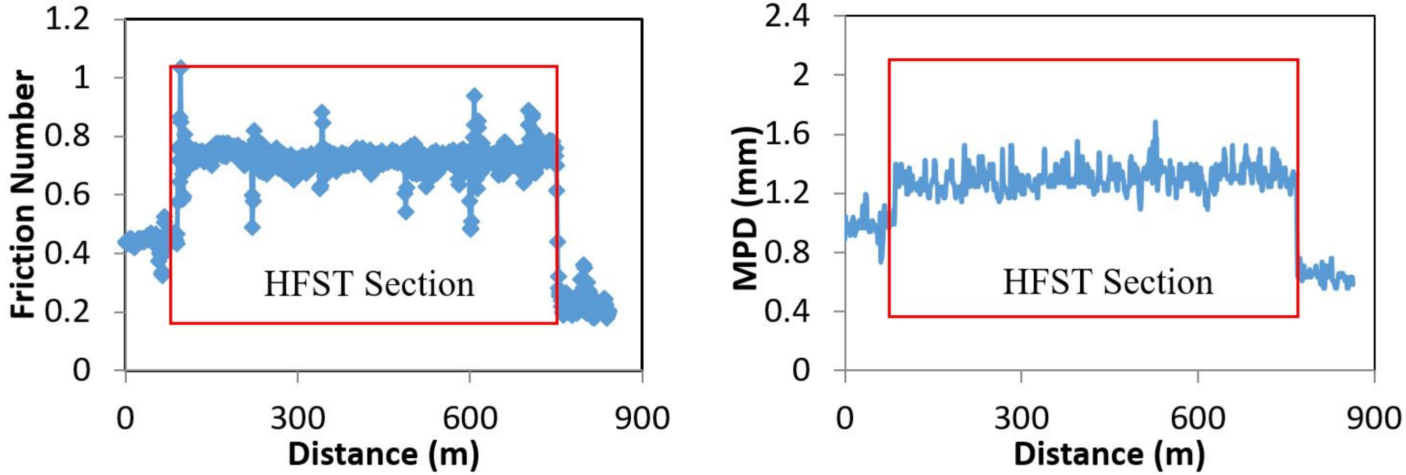
Background

- 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

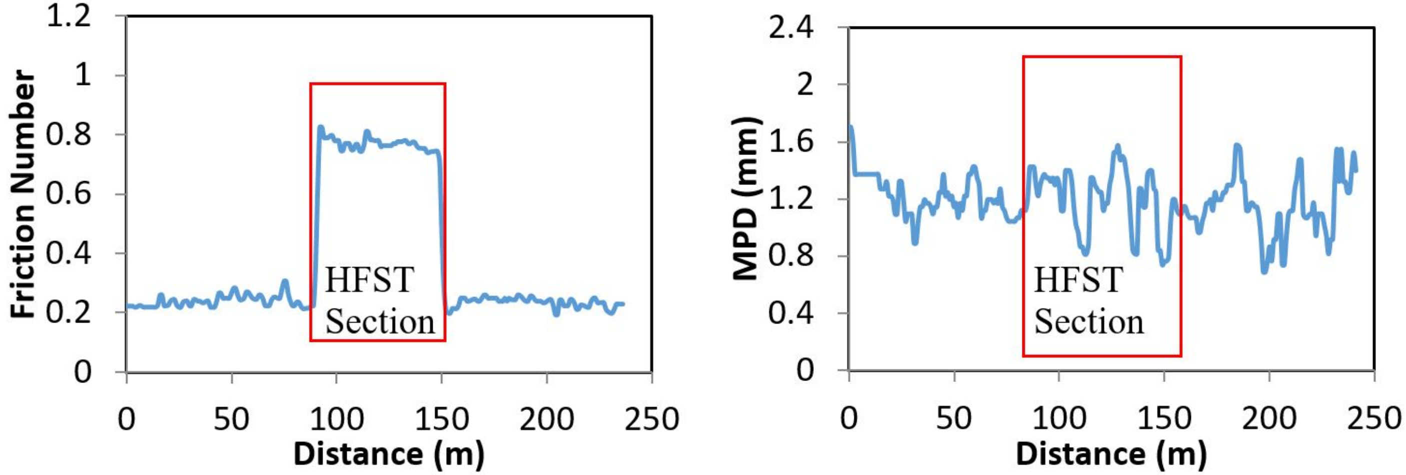
Problem Statement

- 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

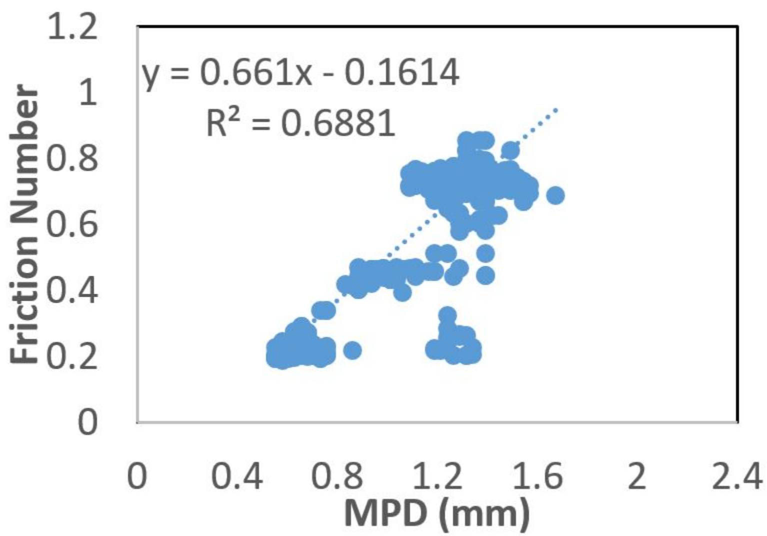


(a) Apparent Friction and MPD Improvement (Site A: IA-I380)

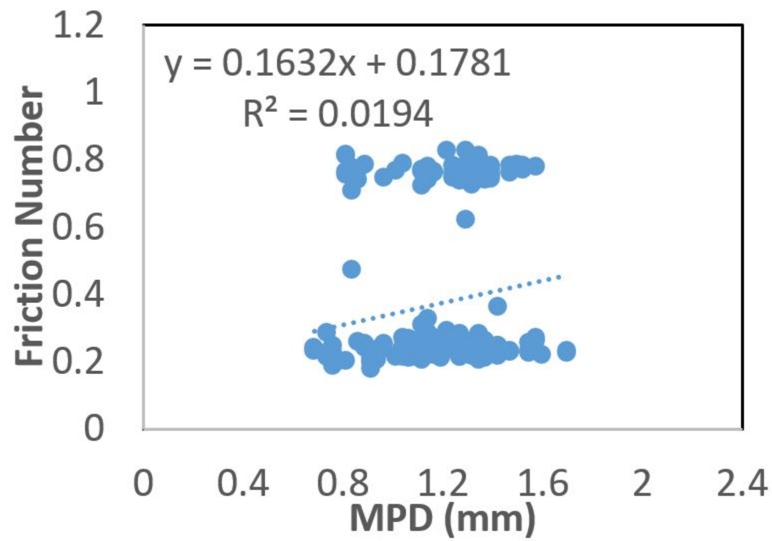


(b) Apparent Friction Improvement but M MPD (Site B: OK-SH20)

Preliminary Result



(a) Site A: IA-I380



(b) Site B: OK-SH20

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

Potential Solutions

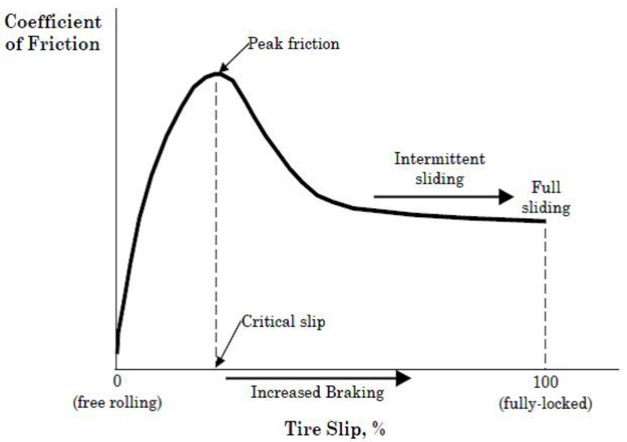
- Novel texture parameters, besides MPD & MTD, which correlate better with friction
  - ✓ From other disciplines, such as mechanical engineering, tire industries, et al.
  - ✓ Use both macro- and micro-texture indicators, combining with field and laboratory (based on surface topography) data sets
- Better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

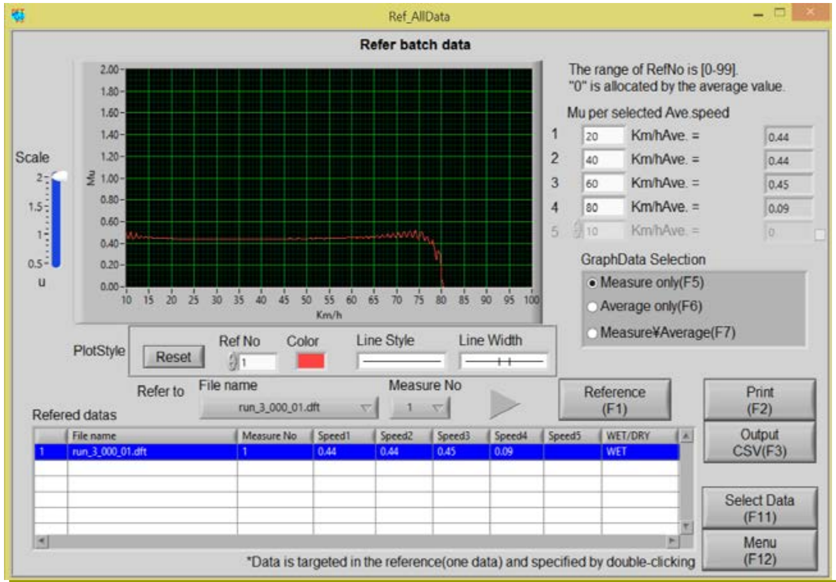
Available Instrument Resources

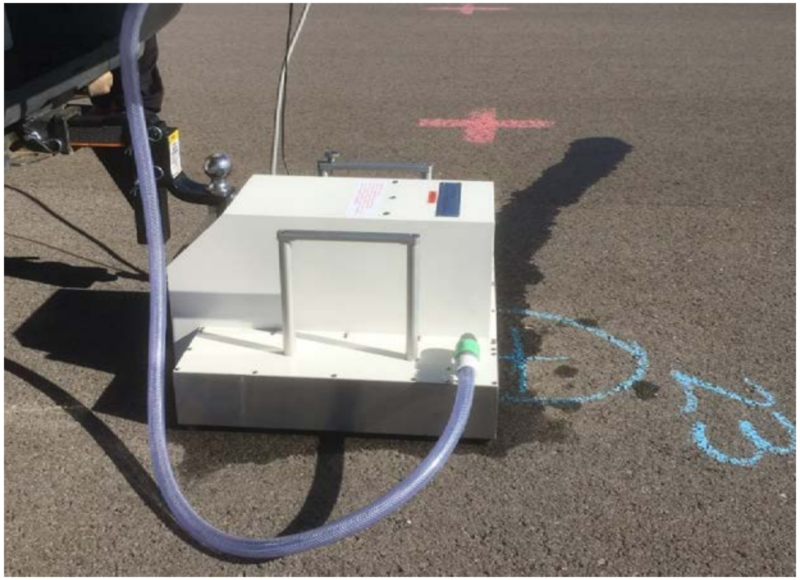
- Grip Tester
  - ✓ Continuously measure longitudinal friction
  - ✓ Operating around the critical slip of an anti-lock braking system
  - ✓ Much shorter testing section length requirement
  - ✓ Airports and highways safety management



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



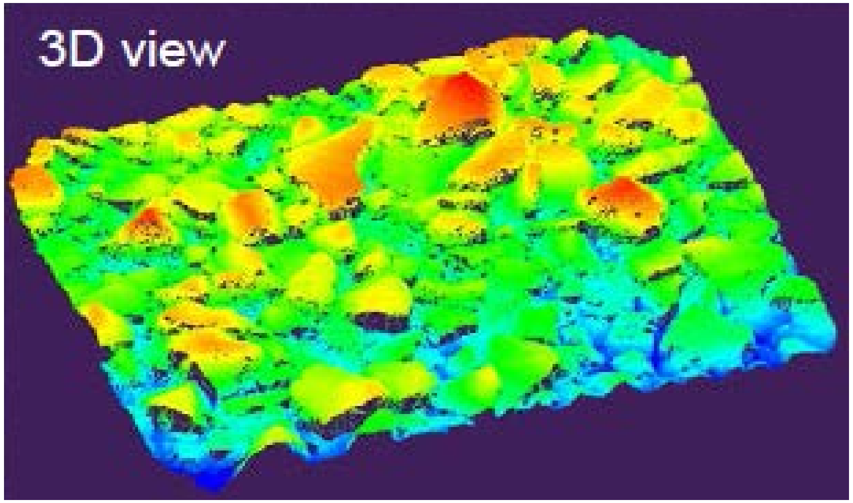


Available Instrument Resources

- 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 x2448
  - ✓ Resolution: 0.01mm (0.0004’’)
  - ✓ Pavement surface micro- & macro-texture



RPUG 2016

- 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

RPUG 2017

- 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

RPUG 2017

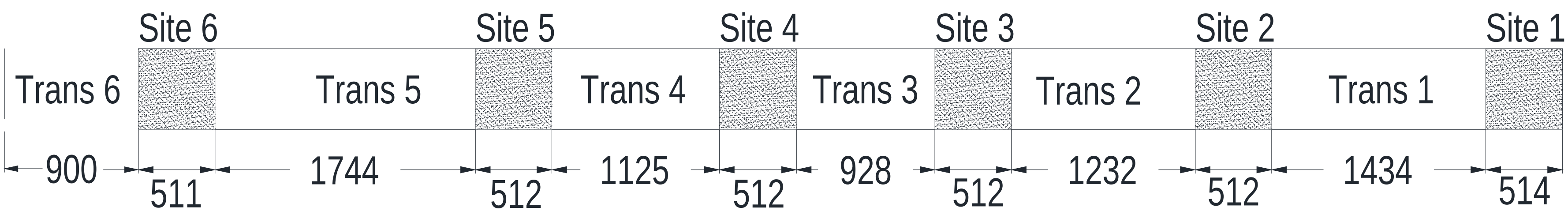
- Deep Learning (DL) based friction prediction model using pavement texture data
    - ✓ Investigate the suitability of DL architectures for friction prediction model
    - ✓ Develop Convolutional Neural Network (CNN), one of the most widely used DL methodologies, for training, validation, and testing
    - ✓ 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

Collect High Resolution 3D Image & Friction Data

Step1: De-noise Image

Clean 3D Image

Step 2: Apply Butterworth Filter

Macro- & Micro-texture

Step 3: Perform Wavelet Analysis

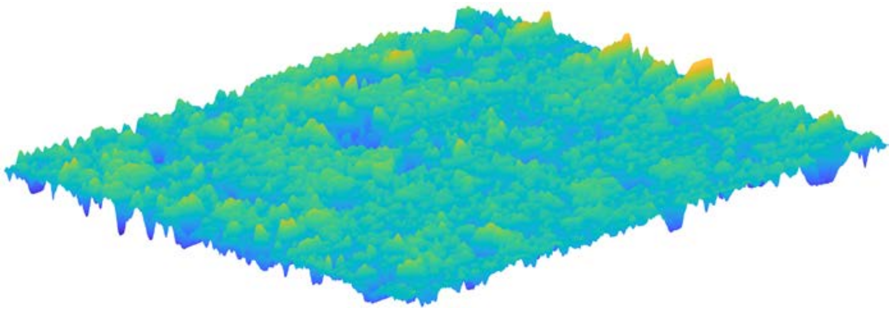
Total Energy Matrix

Step 4: Conduct Correlation Analysis

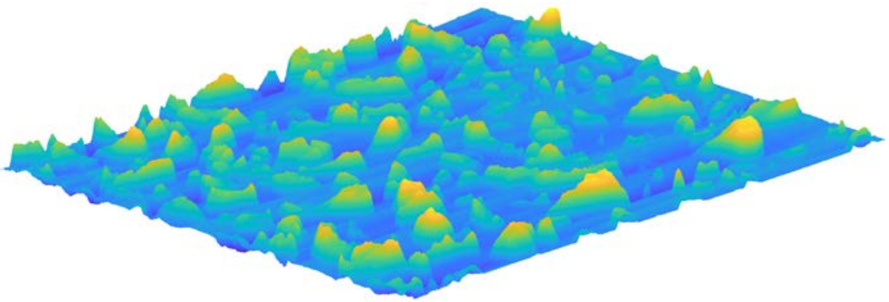
Critical Depth of Pavement

Step 5: Develop Friction Prediction Model

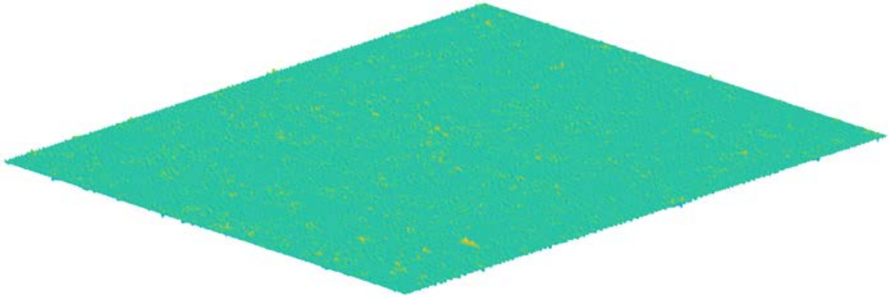
Wavelet Analysis



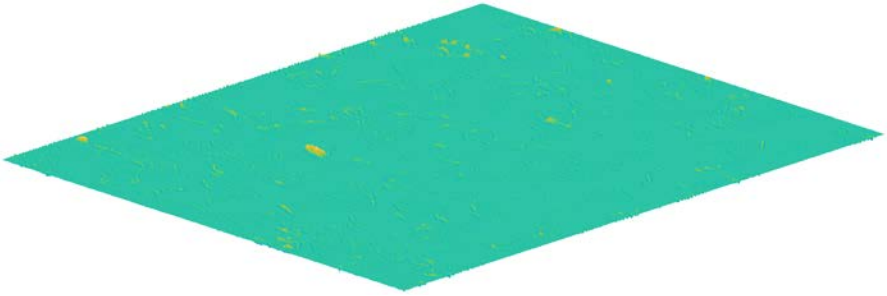
Site 2 – Macro-texture



Site 6 - Macro-texture



Site 2 – Micro-texture



Site 6 - Micro-texture

Butterworth Filter

Wavelet Analysis

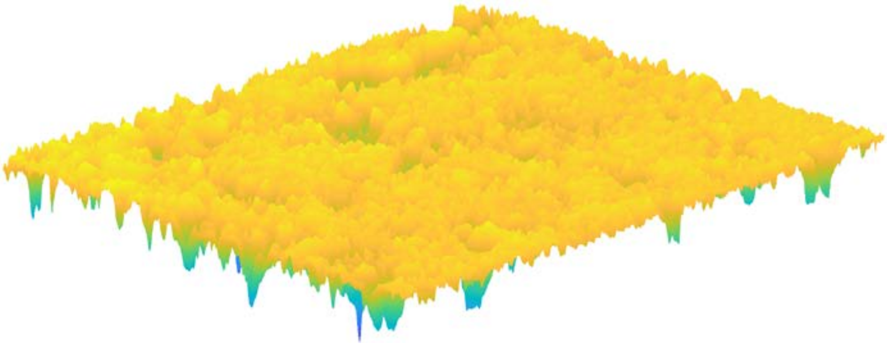
- Decompose macro- & micro-texture into combination of different wavelets

  - ✓ Energy $E_{ni} = \frac{1}{N}\sum_{j,k}(D_{ni}(b_j, b_k))^2$
  - ✓ Total Energy (TE) $TE = \sum_{n=1}^{d} E_{ni}$

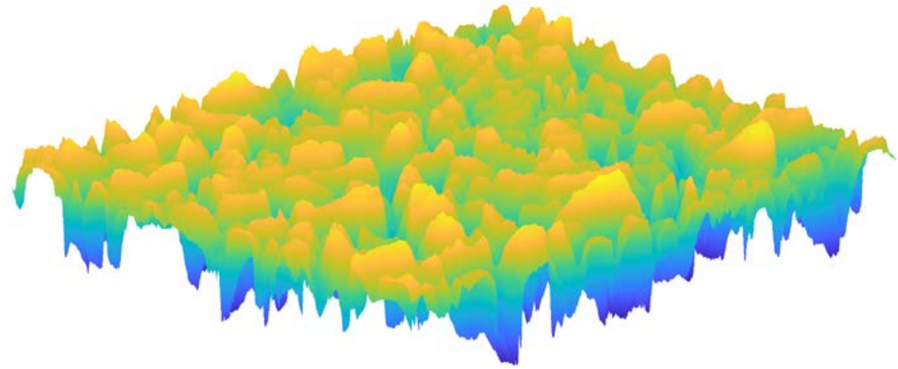
Critical Depth of Texture

- 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 TE_{macro} & TE_{micro} with friction at different DFT speeds: to determine the critical depths at both texture levels

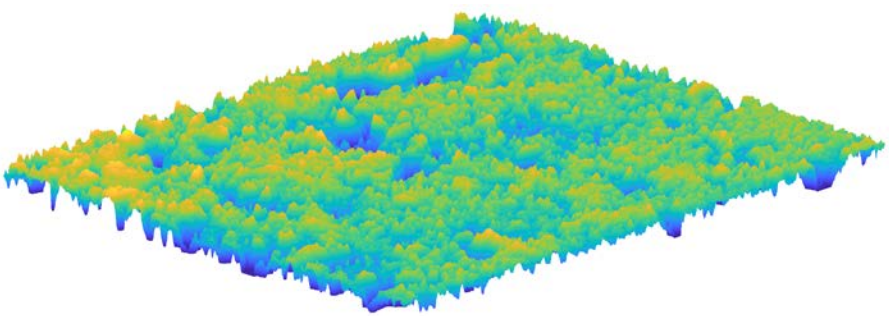
Critical Depth of Texture



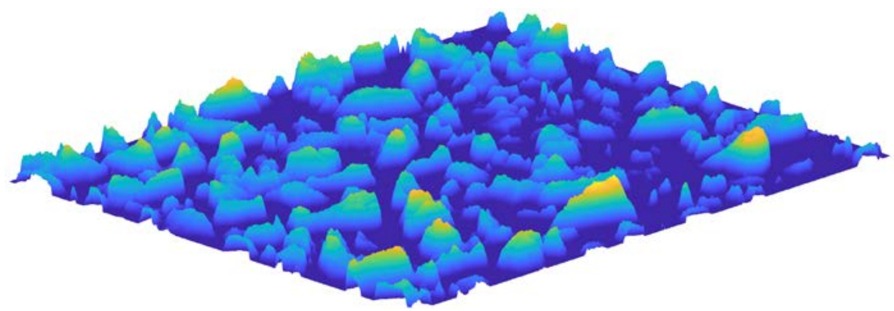
Site 2 – Full range



Site 6 – Full range



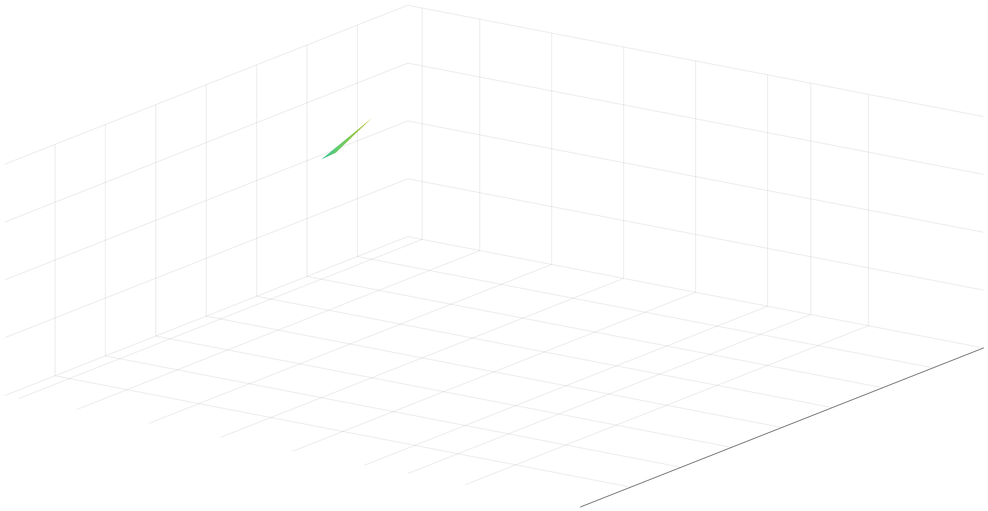
Site 2 – Top 1.4 mm



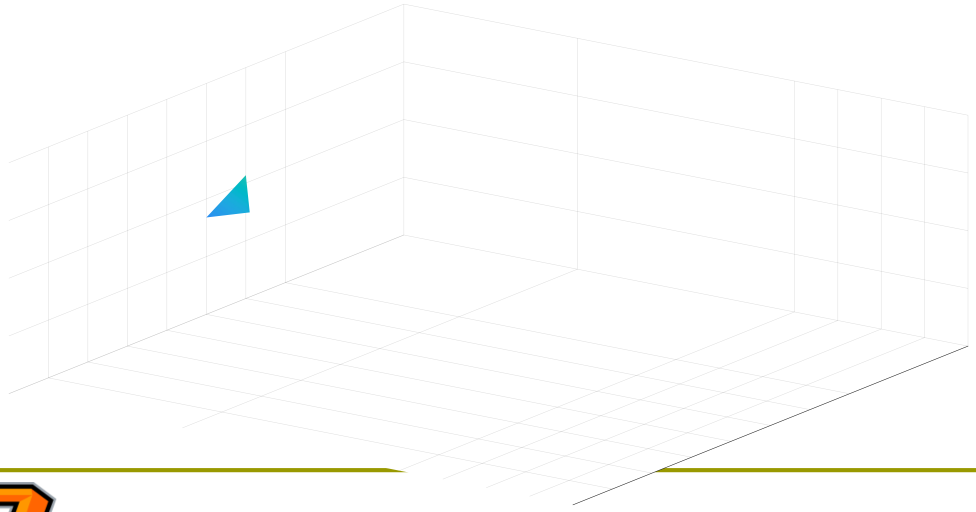
Site 6 - Top 1.4 mm

Top topography analysis of a fractal surface

Critical Depth of Texture



- Macro-texture: 1.4 mm of critical depth



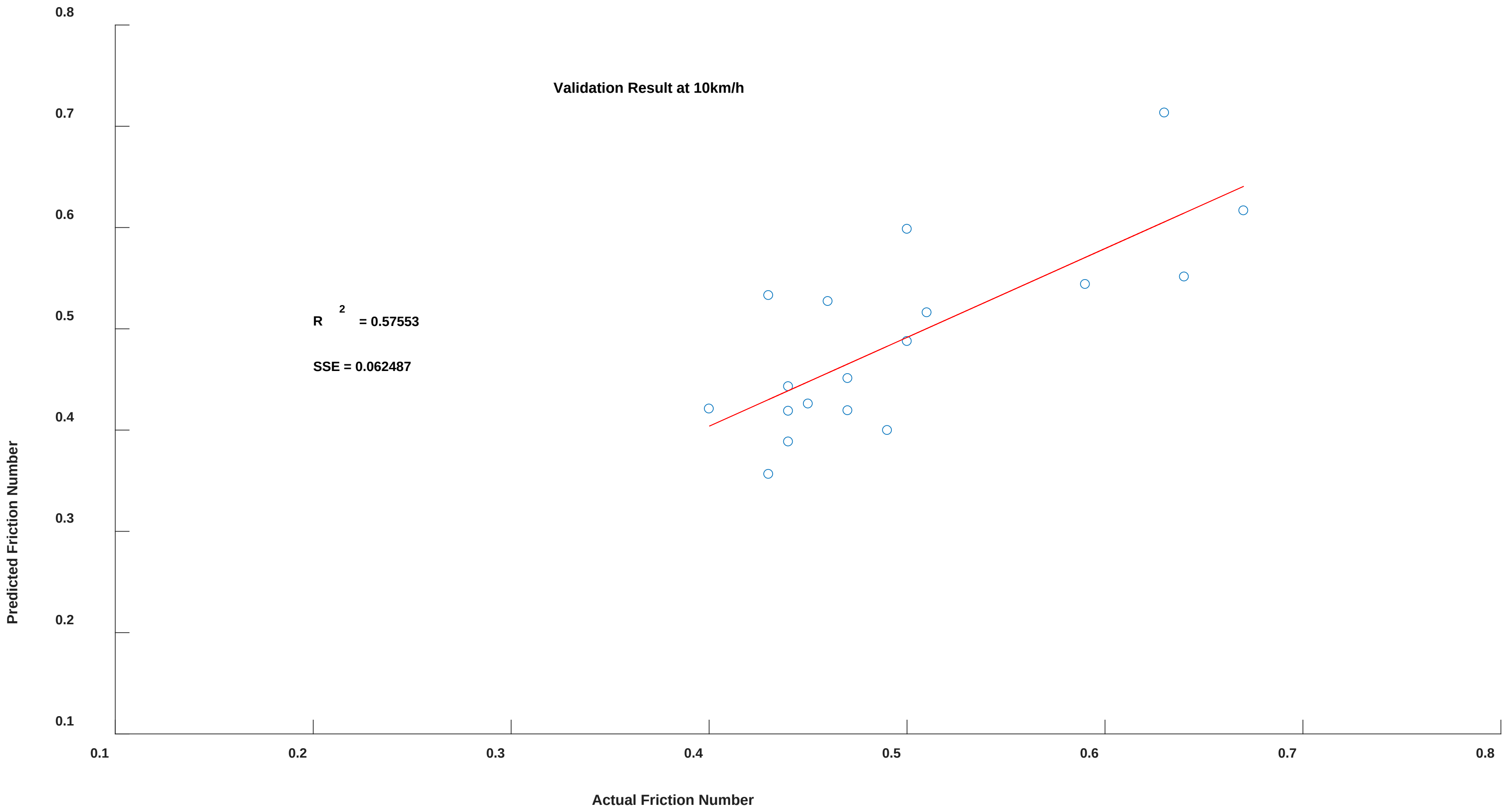
- Micro-texture: 0.5 mm of critical depth

Friction Prediction Model

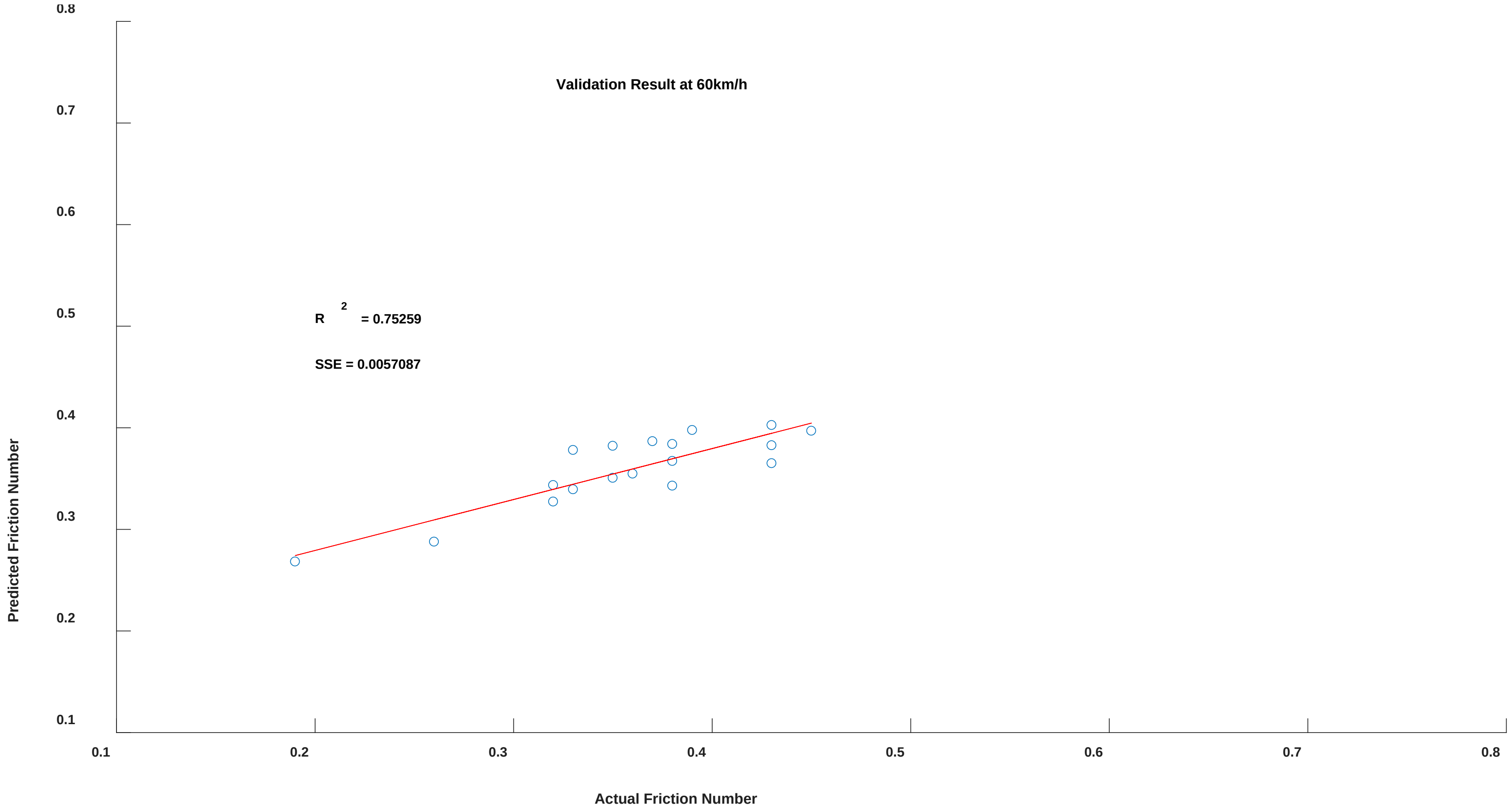
- 72 testing points on LTPP SPS-10: 75% for model development, 25% for validation
- Relate friction to TE_{macro} & TE_{micro} at the critical depth of texture
- Evaluate macro- and micro-texture contributions to DFT friction at different speeds
- Include ambient temperature (T) in the model

$$Friction\ Number = a + \sum_{1}^{2} TE_i * b_i + \mathrm{T} * \mathrm{c}$$

Friction Prediction Model

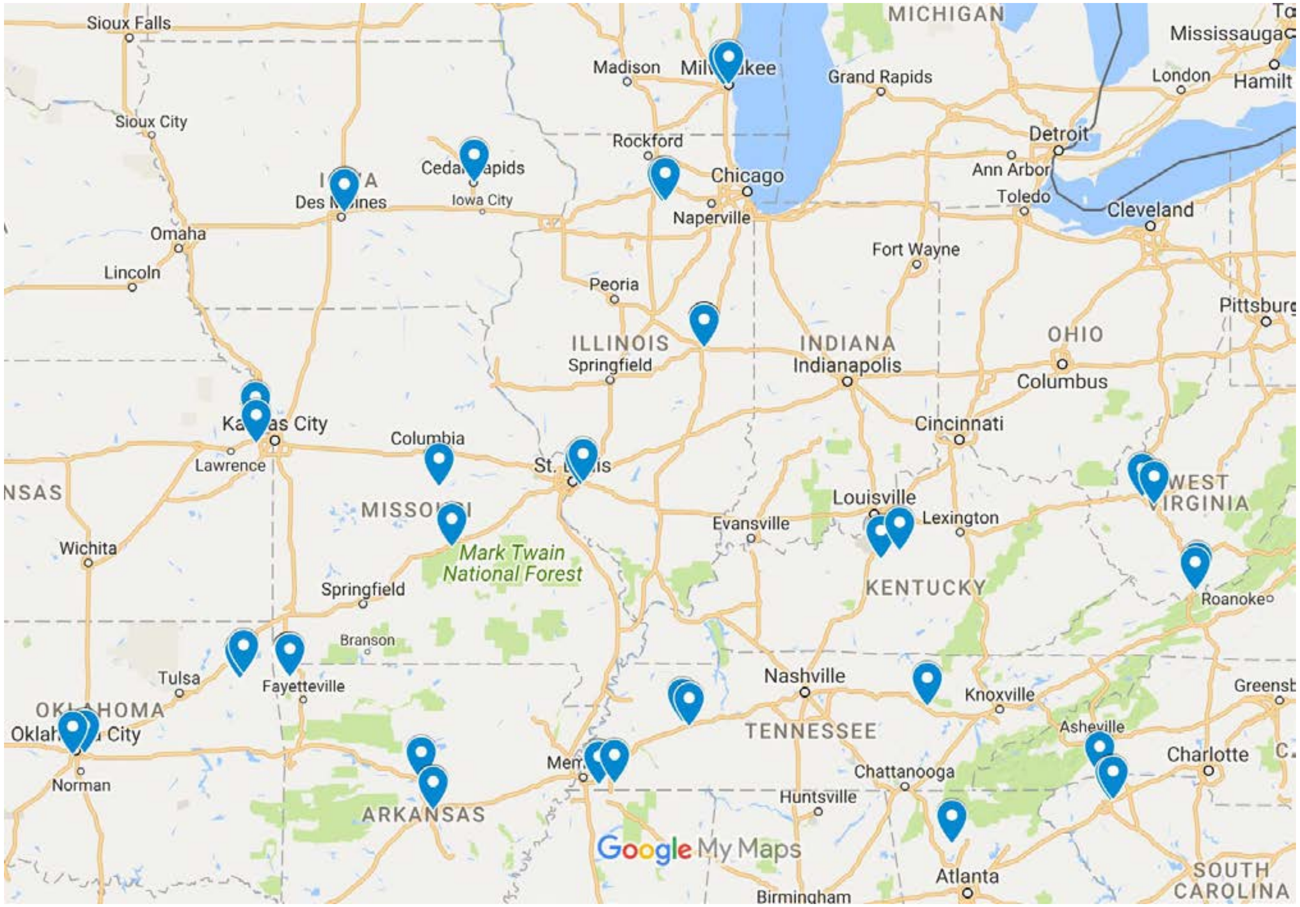


Friction Prediction Model



Part II
Deep Learning based Analysis

Data Source



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

Data Source

HFST Pavement (GA-140)

Flexible Pavement (TN-298)

Rigid Pavement (OK-I44)

Bridge Deck (WV-I64)

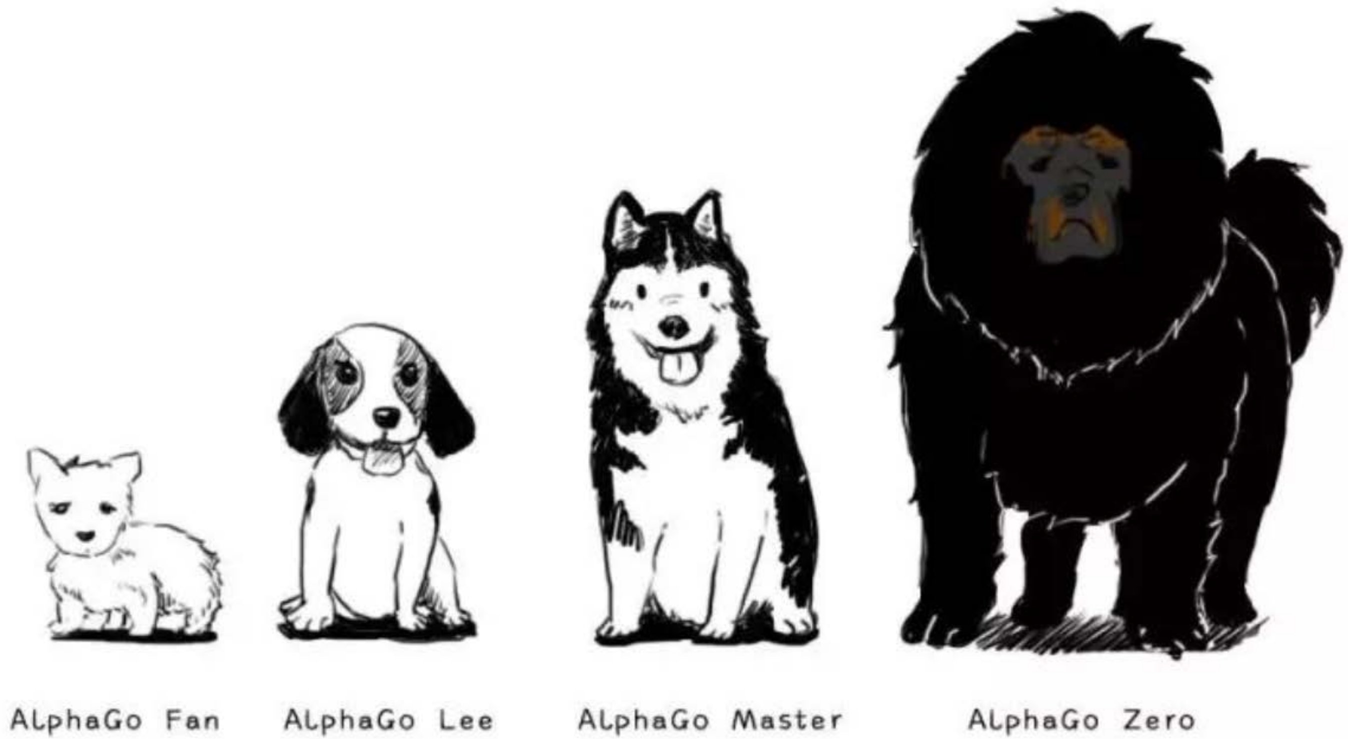
Grooved Flexible Pavement (MO-I44)

Grooved Rigid High Pavement (WI-I94)

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

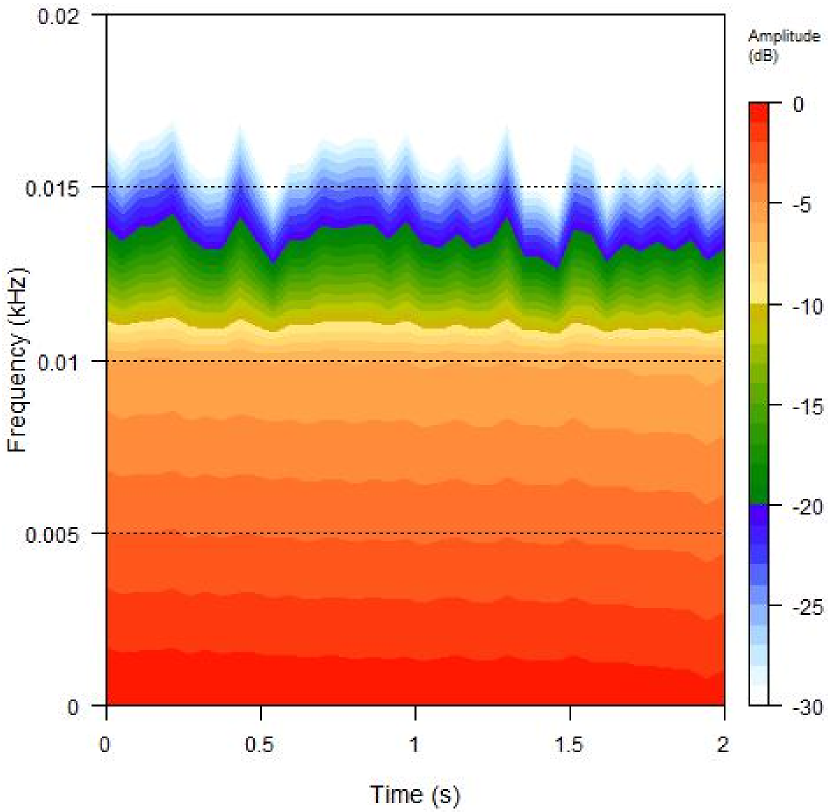
Deep Learning

- “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”



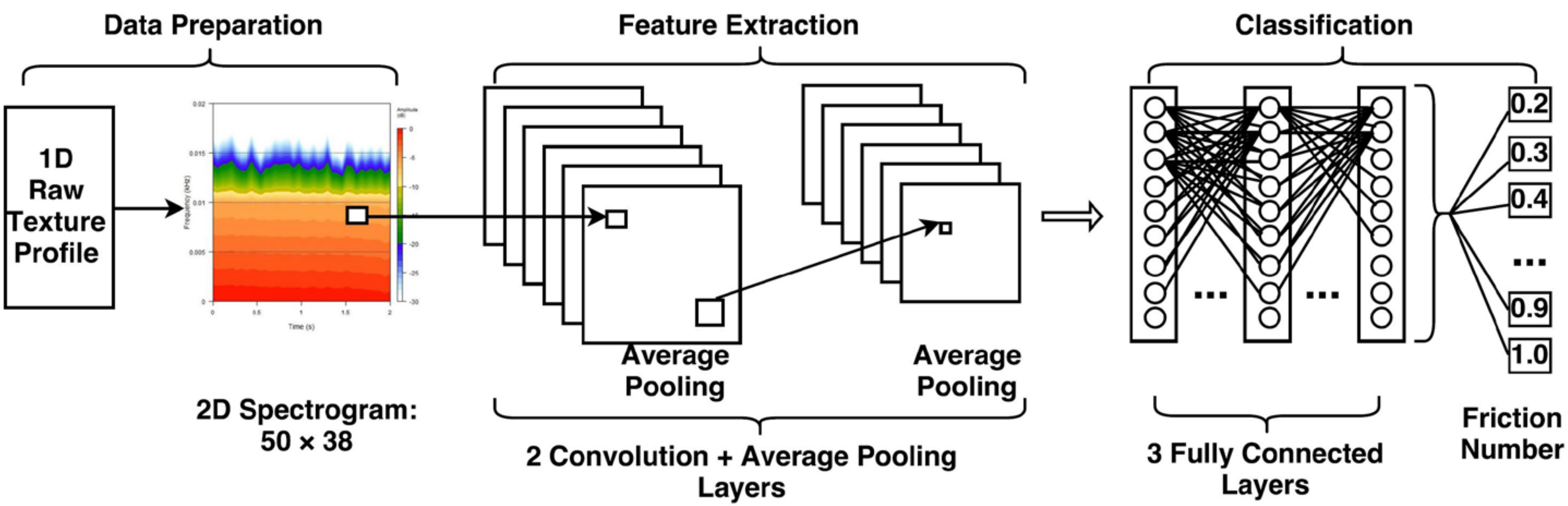
Profile Spectrogram

- 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)

- FrcitionNet 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

Layer	# Parameters
Layer 1: Convolution	640
Layer 2: Convolution	55,392
Layer 3: Fully Connected	540,736
Layer 4: Fully Connected	6,240
Layer 5: Fully Connected	3,104
Layer 6: Output	297
Total	606,409

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

$$\mathrm{CE}(\mathrm{label}, \mathrm{output}) = -\sum_i \mathrm{label}_i \log(\mathrm{output}_i)$$

Training Techniques

- Softmax function: probability distribution of predicted friction number

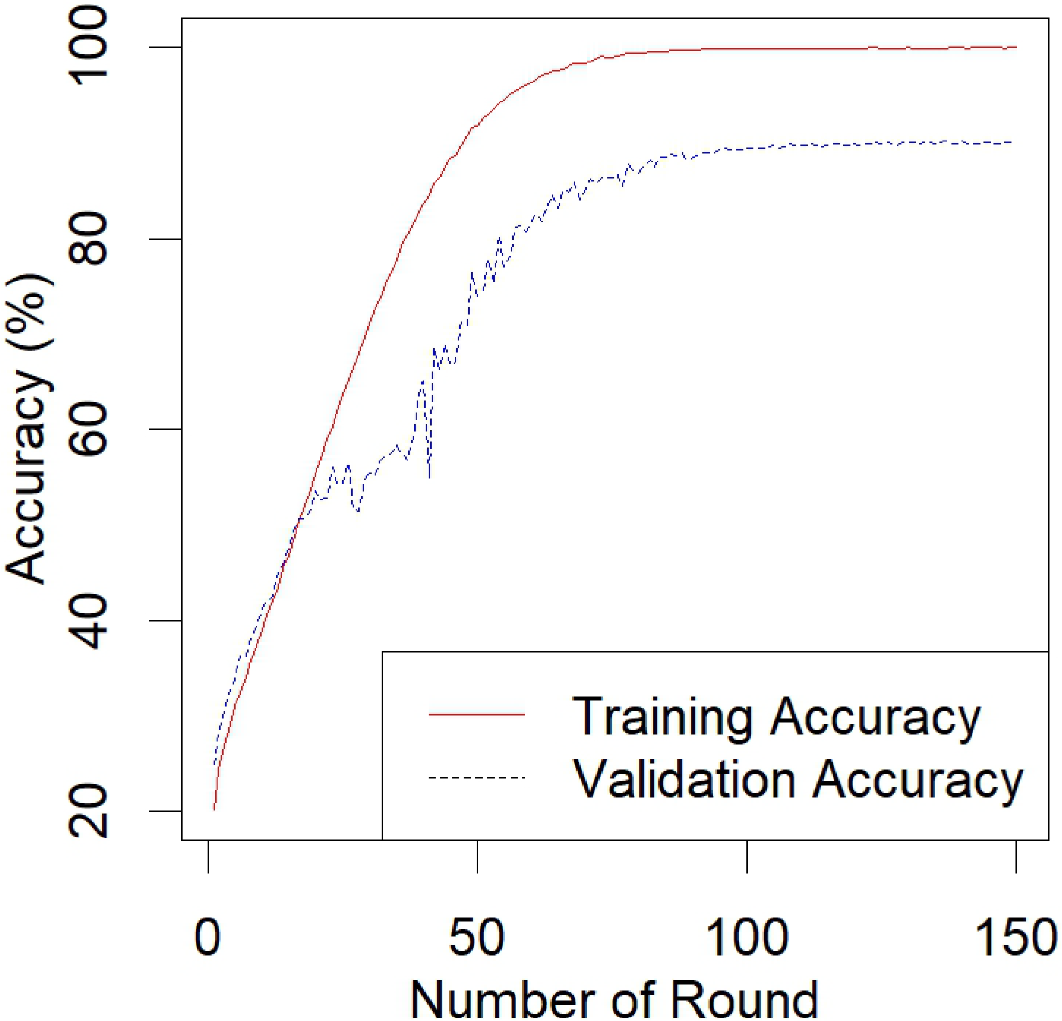
$$\mathrm{softmax}(x)_i = \frac{exp(x_i)}{\sum_j exp(x_j)}$$

- Accuracy: evaluate the goodness of CNN model

$$accuracy(y, \hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1} 1(\hat{y}_i == y_i)$$

Accuracy Summary

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



Conclusions

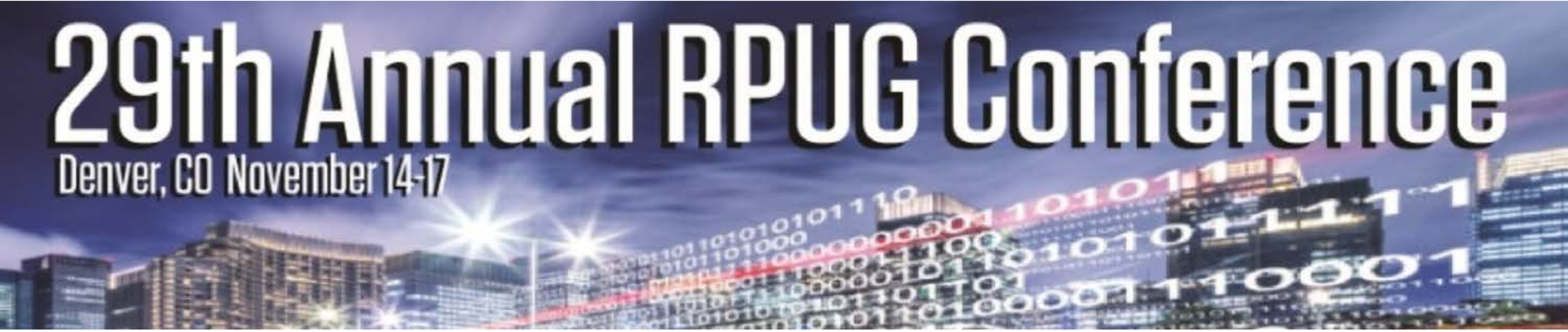
- Top 1.4 mm of pavement texture: critical portion in the context of tire-road contact
- Macro-texture: primarily contributions to friction at high speed
- Micro-texture: governs friction at low speed
- Ambient temperature: significant factor for friction performance

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

Acknowledgements

- Federal Highway Administration (FHWA)
- Oklahoma Department of Transportation (ODOT)



Questions ?

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