Data Automation for Pavement Distress Survey in the 3D World

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Two Parts

Current 3D System Highway □ Airfield New Developments/Challenges Inertial Sensor for IRI (WIS) Deep-Learning Plan

Part One

Current 3D System



PaveVision3D Ultra (3D Ultra)



3D Ultra Vehicular Platform



1mm Resolution 3D Pavement Surface





1mm Resolution 3D Pavement Surface



3D Data Collected at 100KPH





3D Data Collected at 100KPH



3D Data Collected at 100KPH



Automated Processing



Automated Processing



Automated Processing



Inspection of Airport Runway



Airport Runway Data



Runway PCI Analysis



Runway PCI Analysis





Objectives: Groove Evaluation

- To develop algorithms to automatically estimate the runway groove dimension
 - Groove Depth
 - Groove Width, and
 - Groove Spacing
- To evaluate runway groove performance based on AC 150/5320-12C

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Profile Data Filtering



Geometry Contour Algorithm



- Red Box Moving Window
- Blue Circle Deepest Point in the Moving Window

Backward & Forward Traversal

- Determine the starting & ending points of grooves based on changes of gradient /slope
- Use to measure groove dimensions



Groove Dimension Estimation



Groove Volume Estimation



$$V = \sum_{i=1}^{n} (f(xi) - y_i) * \Delta x * \Delta z$$

Algorithm Validation



Algorithm Validation



Grooves Identification Based On One Single Profile

Algorithm Validation



Grooves Identification Based On All Profiles

Groove Evaluation

Groove Depth or Width Distribution Range (mm)	Full Lane based Scenario			
	Width		Depth	
	Frequency	Percentage %	Frequency	Percentage %
$<\frac{3}{16}$ in. (< 4.76 mm)	1366	0.7 %	34011	17.32 %
$\geq \frac{3}{16}$ in. (≥ 4.76 mm)	16837	99.30 %	102448	82.68 %
$\geq \frac{1}{4}$ in. (≥ 6.35 mm)	17952	90.73 %	56394	30.51 %
$\geq \frac{5}{16}$ in. (≥ 7.94 mm)	160213	81.59 %	3515	1.79 %



Part Two

New Developments/Challenges



WIS Inertial Module for Longitudinal Profiling



WIS Inertial Module



A self-contained, fist-size inertial sensor designed & developed by Dr. Wang's team

Integrated into PaveVision3D sensor case

Built-in: hardware filtering & power

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Profile Measurement Principle



Image Reference: Description and Evaluation of the South Dakota Road Profiler

Validation Tests: 3 Pavement Sections



Testing Site I W Lakeview Rd. and Driving Speed 30 mph



Testing Site II Country Club Rd and Driving Speed 40 mph



Testing Site III W 6th Ave and Driving Speed 60 mph

Test Site I: W Lakeview Rd 12 Passes

Repeatability of 3D Data From Left and Right Side (WIS)



Test Site I: W Lakeview Rd **10 Best Passes** Repeatability of 3D Data From Left and Right Side (WIS)



Test Site : W Lakeview Rd 12 Passes Repeatability of Profile Data From Left and Right Side (WIS)



Test Site I: W Lakeview Rd 10 Best Passes

Repeatability of Profile Data From Left and Right Side (WIS)


Test Site I: W Lakeview Rd 12 Passes

Repeatability of Profile Data From Left Side (Ames)



Test Site I: W Lakeview Rd 10 Best Passes

Repeatability of Profile Data From Left Side (Ames)



Test Site I: W Lakeview Rd 12 Passes

Continuous IRI Results

- Calculate an IRI Result in Every Small Distance, e.g. 25 ft., from the First Point to the Last Point of the Profile.
- Plot the Calculated IRI Results into a Continuous Curve.
- Displayed WIS data and Ames data From the Second Pass.



Test Site II: Country Club Rd 11 Passes

Repeatability of 3D Data From Left and Right Side (WIS)



Test Site II: Country Club Rd 10 Best Passes Repeatability of 3D Data From Left and Right Side (WIS)



Test Site II: Country Club Rd 11 Passes

Repeatability of Profile Data From Left and Right Side (WIS)



Test Site II: Country Club Rd 10 Best Passes

Repeatability of Profile Data From Left and Right Side (WIS)



Test Site II: Country Club Rd 11 Passes ■ Repeatability of Profile Data From Left Side (Ames)

			Profile Synchronization: Correlation Analyze Apply Offsets Navigate
Left Side			File Relative Maximum Offset (ft) Correlation (%) (%) Ames R1 -0.16 96.4 Ames R1 0.09 97.9
Avg %	Max %	Min%	Ames Rill 0.09 98.7 90 Ames Rill 0.09 98.7 90 Ames Rill 0.00 98.9 70
97.19	98.9	93.3	Amer.86 0.00 96.6 § 60 Amer.87 0.09 97.4 § 50 Amer.88 0.09 93.3 40 40
			30 20 10 10 10 10 10 10 10 10 10 1

Test Site II: Country Club Rd 10 Best Passes

Repeatability of Profile Data From Left Side (Ames)



Test Site II: Country Club Rd 11 Passes

Continuous IRI Results

- Calculate an IRI Result in Every Small Distance, e.g. 25 ft., from the First Point to the Last Point of the Profile.
- Plot the Calculated IRI Results into a Continuous Curve.



Displayed WIS data and Ames data From the Fifth Pass.

Test Site III: W 6th Ave 12 Passes Repeatability of 3D Data From Laft and Right Side (W



Test Site III: W 6th Ave 10 Best Passes

Repeatability of 3D Data From Left and Right Side (WIS)



Test Site III: W 6th Ave 12 Passes

Repeatability of Profile Data From Left and Right Side (WIS)



Test Site III: W 6th Ave 10 Best Passes

Repeatability of Profile Data From Left and Right Side (WIS)



Test Site III: W 6th Ave 12 Passes

Repeatability of Profile Data From Left Side (Ames)

Avg %

95.43



Test Site III: W 6th Ave 10 Best Passes

Repeatability of Profile Data From Left Side (Ames)

			Profile	Synchro	onization: C	orrelation Analyze Apply Offsets Navigate	•
			File	Relative Offset (ft)	Maximum Correlation (%)		
Left Side			Ames_R10 Ames R11	0.09	95.3 95.7	100	
			Ames_R12	-0.24	95.5 97.6	80	
Avg %	Max %	Min%	Ames_R3 Ames_R4 Ames_R6 Ames_R8	-0.16 -0.08 0.00 -0.32	95.4 93.0 95.3 97.1		
95.52	97.6	93.0	Ames_R9	0.00	94.8		
						-5 -4 -5 -2 -1 0 0 ffset (ft) 	•
						(

Test Site III: W 6th Ave 12 Passes

Continuous IRI Results

- Calculate an IRI Result in Every Small Distance, e.g. 25 ft., from the First Point to the Last Point of the Profile.
- Plot the Calculated IRI Results into a Continuous Curve.
- Displayed WIS data and Ames data From the First Pass.



Deep-Learning Plan



Objectives of Pavement Distress Recognition

Detection

 Find the Actual Location of Distresses with Pixel-Perfect Accuracy
 Classification

Label Distress Type

Challenges in Pavement Distress Recognition

Complexity

Pavement Surface: A highly Complicated Distress Identification: Even Human **Operator Has to Be Well-Trained** Diversity Diverse Pavement Surface Textures Various Presences of Pavement Distresses



Common Failures in Distress Automation

Inconsistent Accuracies for Different Roads



Common Failures in Distress RecognitionInterference from Other Patterns



Deep Learning: Potential for Automated Distress Recognition

- Strong Learning Ability
 - Learning from Experiences;
 - Exploiting Understanding on New and Unlabeled Examples;
- Versatility
 - A Single Deep Learning Network Can Detect Multiple Types of Pavement Distresses
- Enhanced Reliability
 - Feed with Exhaustive Variations of Pavement Distresses

History of Deep Learning

- □ 1940s-1960s
 - Cybernetics
 - Biological Learning & Models Using Single Neuron
- □ 1980s-1990s
 - Connectionism/Neural Network
 - 1 or 2 Hidden Layer
 - Backpropagation
- □ 2006-Now
 - Deep Learning
 - Many Layers & Massive Neurons

Trends of Deep Learning

Increasing Model Size



Goodfellow et al., Deep Learning, 2016)

Compositional Model for Image Recognition



Goodfellow et al., Deep Learning, 2016)



Current Status of Image Recognition Using Deep Learning

Achievements

- Give descriptions on what objects have been detected in an image;
- Detect the bounding box encloses the object and Label the type of detected object within the bounding box
- Limitations
 - Actual location of the detected object is vague;
 - Lack of Pixel-perfect Accuracy

Deep Learning Models for Pavement Distress Recognition

Alternative #1

- Deep Convolution Neural Network
 - Feed Forward
 - Detect whether an image cell has distresses
- Recurrent Neural Network
 - Feed Backward
 - Find which pixels in a detected image cell are very likely to be distress pixels

Deep Convolution Neural Network & Recurrent Neural Network



Types of Filters Used in Convolution Neural Network

- Matched Filters
 - Objective: detect the profiles of a crack;
 - Multiple Orientations: detect cracks oriented at various directions;
 - Multiple Filter Sizes and Spreads: detect cracks with various widths.
- Gabor Filters
 - Objective: detect the edges of a crack
 - Multiple Orientations: detect edges oriented at various directions;
 - Multiple Degrees of Smoothing and Enhancement

Convolution Using Matched Filter



Convolution Using Gabor Filter



Deep Neural Network for Pavement Distress Recognition



Image Library for Pavement Distress Recognition

- Data Type
 - 3D Data & 2D Images
- Image Library Size
 - 2016-2017: 150,000 3D Images + 150,000 2D Images
 - 2017-2020: 1,000,000 3D Images + 1,000,000 2D Images
- Ground Truth
 - Manually Marked
- Diversity
 - All Typical Variations of Pavement Distresses

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Typical Samples in Image Library



Challenging Tasks

Architecture of Deep Learning Network

Structure of Neurons at Each Layer, Connection between Layers

Exhaustive Image Library

- 3D Pavement Data & 2D Pavement Image
- All Variations of Pavement Distresses, Manually Marked Ground-truth

Long-term Training & Optimization

- Training on Each Layer, on Connections between Layers, Entire Network
- Sufficient Computational Horsepower

Self-taught Learning

- Unsupervised Learning from Unlabeled Data;
- Progressive Improvements in Real-time Applications

Real-time Application

Parallel Computing to Reduce Processing Time
Funding Support

Federal Highway Administration (FHWA)
Federal Aviation Administration (FAA)
University Transportation Centers (UTC)
Oklahoma DOT, Arkansas DOT, Indiana DOT
Users in South Africa, Brazil, China, and Europe
Oklahoma State University



Thank You!

