Distress Image Library for Precision and Bias of Fully Automated Pavement Cracking Survey

Kelvin C.P. Wang, Ran Ji, and Cheng Chen
kelvin.wang@okstate.edu
Oklahoma State University/WayLink
School of Civil and Environmental Engineering

Pavement Evaluation 2014
Blacksburg, VA

Outline

- Challenges of Distress Detection
- Benchmark Database and Evaluation Methods
- Case Studies of Algorithm Comparison

Manual Distress Survey

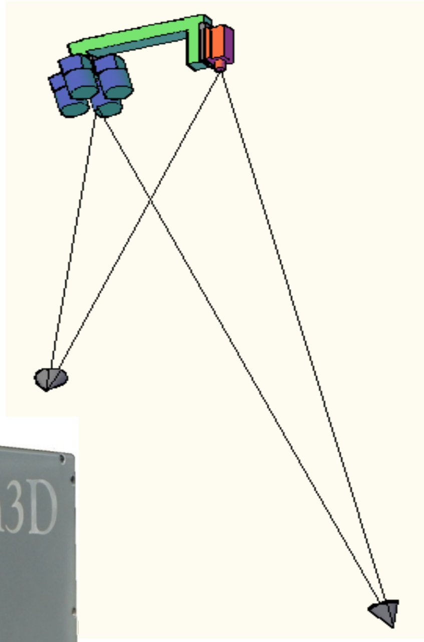
- Tedious manual measurement and rating processes
- Substantial manpower
- Access to pavement
- Traffic control
- Difficult or inconvenient in archiving and retrieving detailed quantitative information

Photo from: https://www.nevadadot.com/About_NDOT/NDOT_Divisions/Planning/Aviation/Pavement_Condition_Index.aspx

Challenges of Cracking Survey

- Analysis and Processing
  - Detection/Identification
  - Classification
- Precision and Bias
  - Reference???

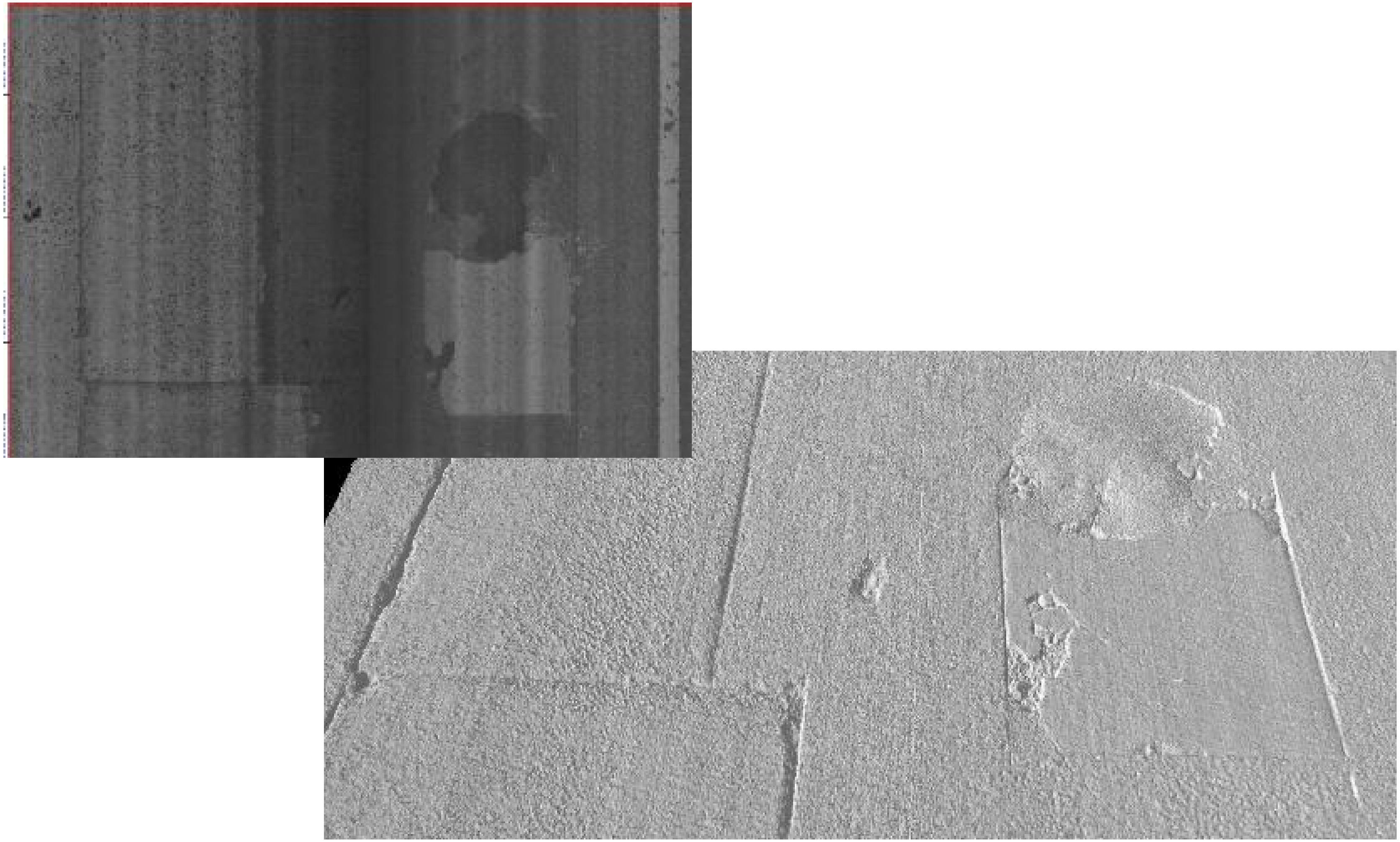
PaveVision3D Ultra Systems



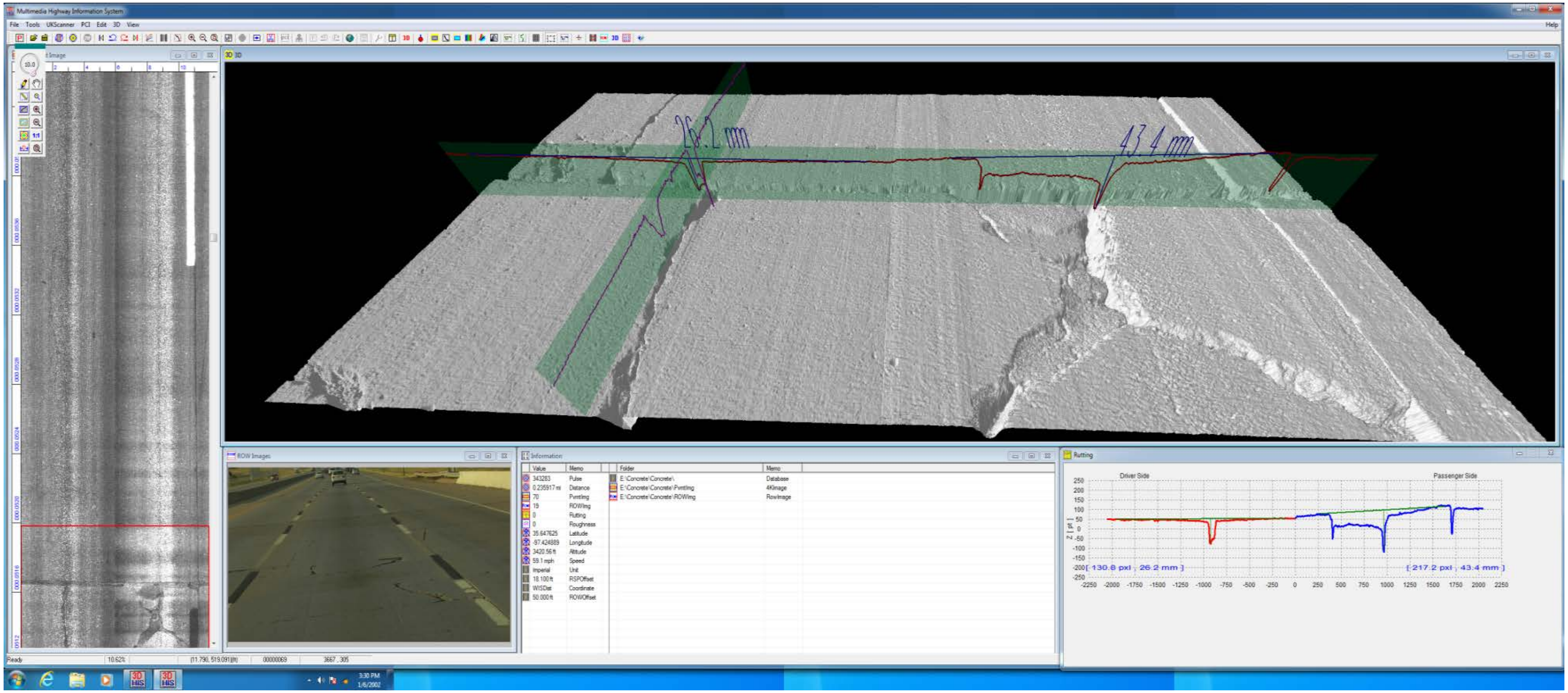
PaveVision3D Ultra - New

Green Lasers for 3D Ultra

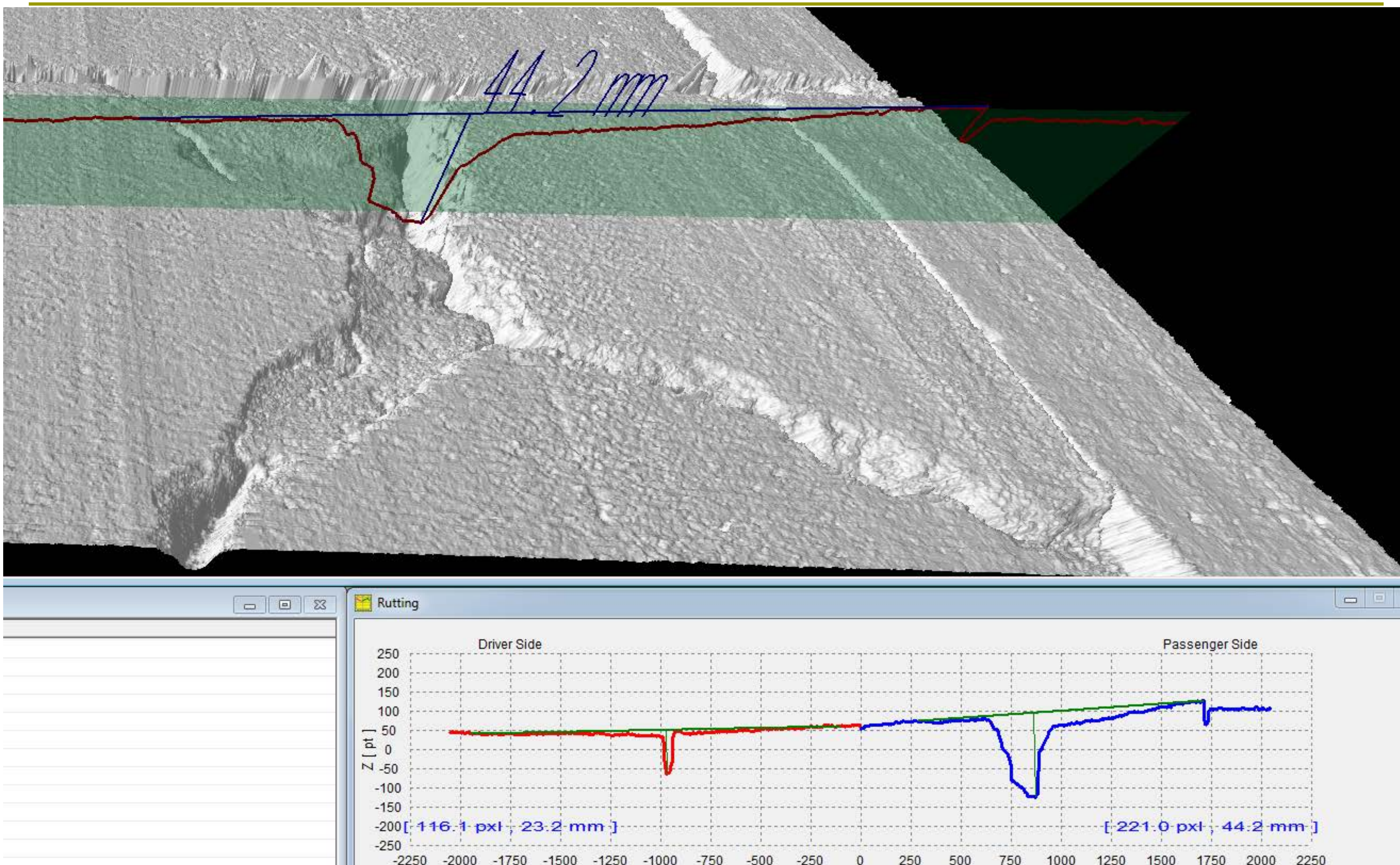
3D Ultra Data at 60MPH (100KM/h)



3D Data at 60MPH (100KM/h)



3D Data at 60MPH (100KM/h)



3D Ultra Current Status

- Sensor technology: mature
- Challenges to software solutions
  - To be simple and usable to pavement engineers
  - Confidence in quality of data
  - Utilization and analysis of 1mm data sets

Data Analysis Challenges

- Detection Algorithms
  - Accuracy
  - Robust
  - Fast
- Result Evaluation
  - No benchmark database
  - No wide accepted evaluation criteria

Evaluation Methods

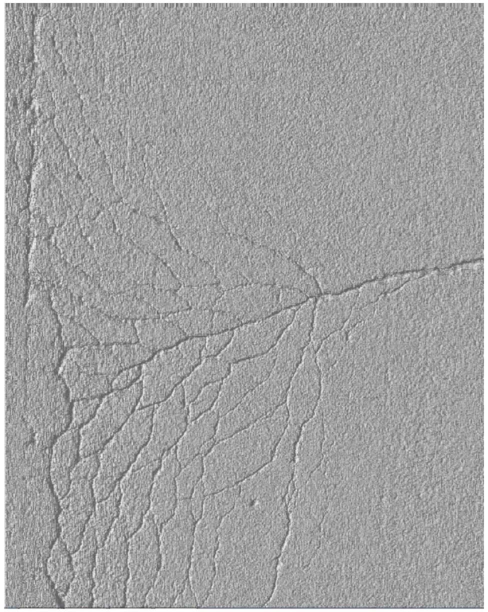
- Desired distress detection algorithms
  - Fast
  - Achieve high scores in both precision and recall rate

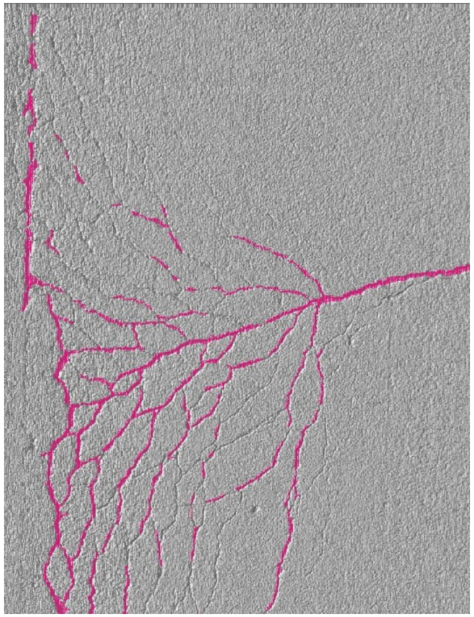
Need of Image Library

- What is the reference?
- Is there a “Ground-Truth”?
- What to use in benchmarking?
- Therefore: an Image Library
  - Manually developed with marked cracks
  - Multiple-checking for precision/bias
  - Expensive; but necessary

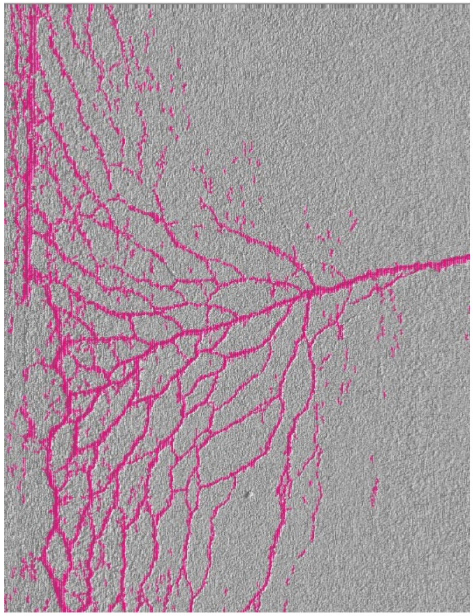
Precision Recall Analysis

- Precision: correctly identified cracks over total identified cracks
- Recall: correctly identified cracks over total crack



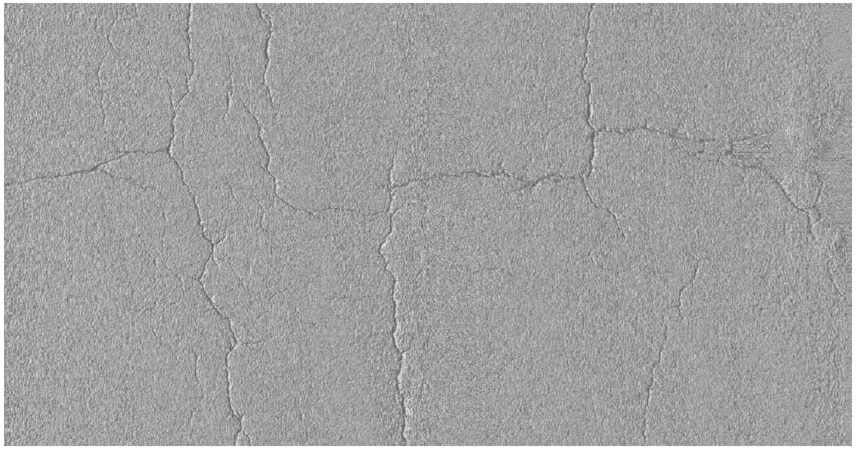


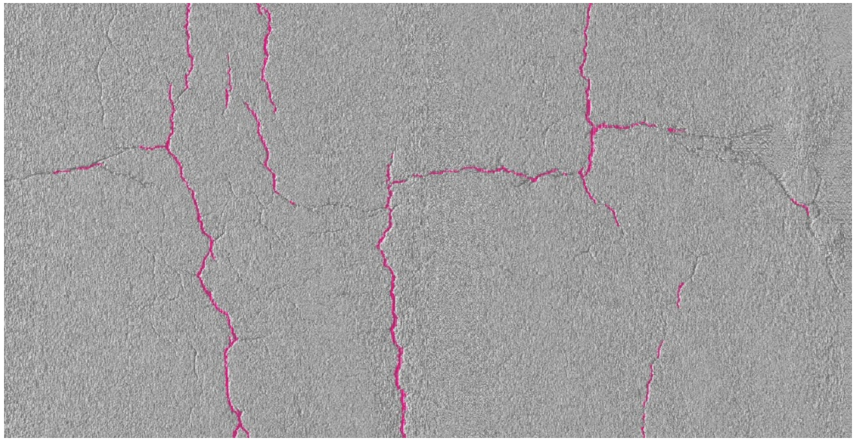
Example of good precision score



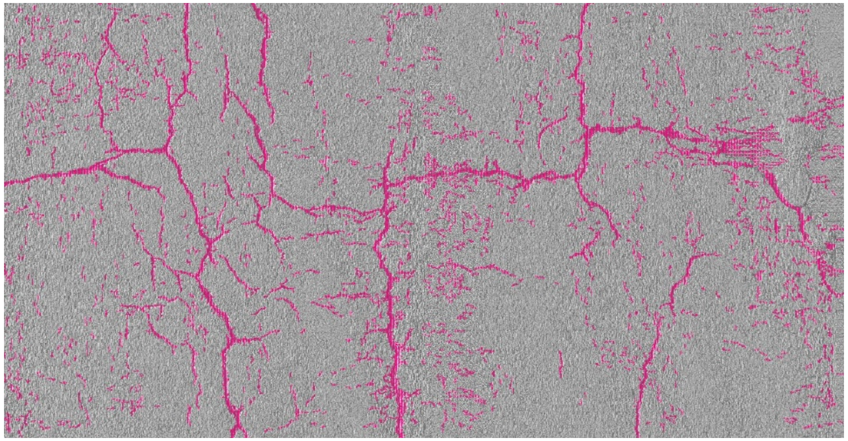
Example of good recall score

Precision Recall Analysis





Example of good precision score



Example of good recall score

Precision Recall Analysis

- Confusion Matrix

	Actual positive	Actual negative
Predicted positive	True Positive	False Positive
Predicted negative	False Negative	True Negative

	Crack	Non-crack
Predicted crack	True Positive	False Positive
Predicted non-crack	False Negative	True Negative

Precision Recall Analysis

		actual value		
		p	n	total
prediction outcome	p'	True Positive	False Positive	P'
	n'	False Negative	True Negative	N'
	total	P	N	

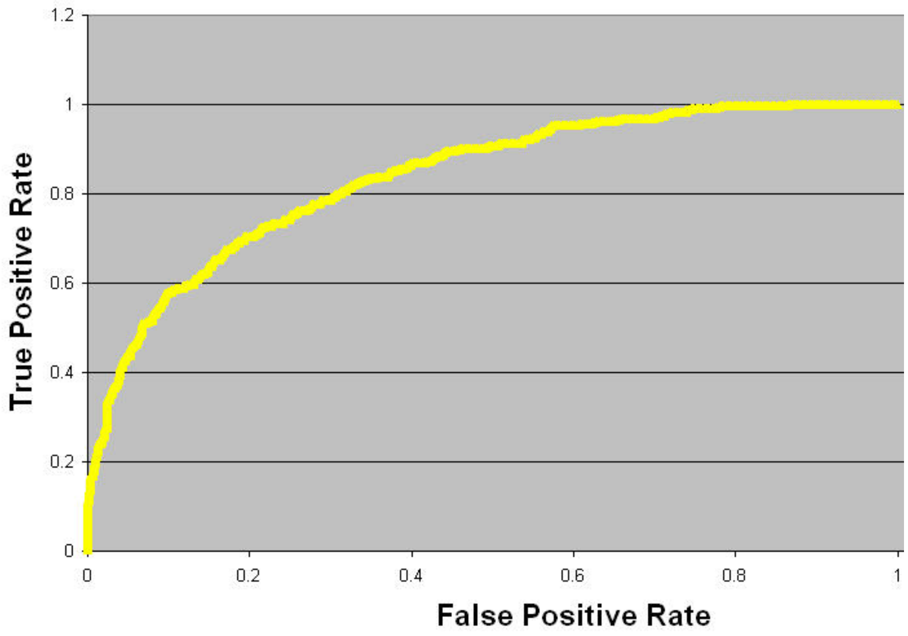
$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$\text{F} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

ROC Curve

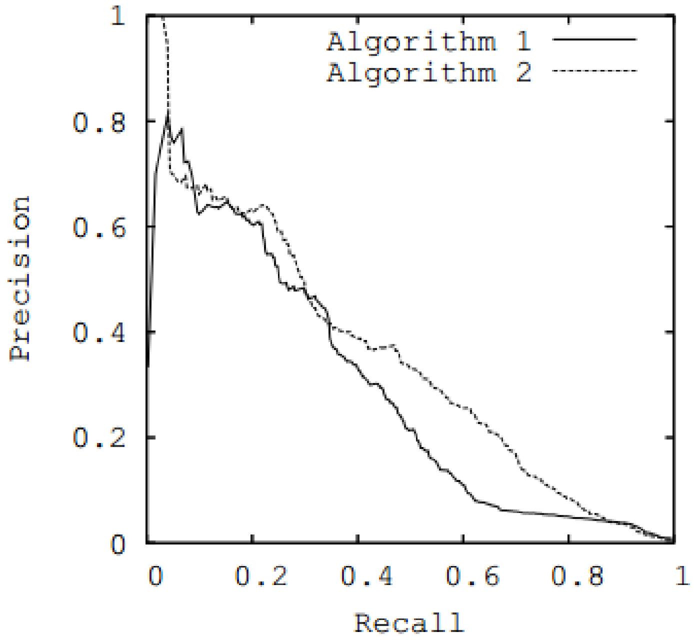
- Receiver Operating Characteristic (ROC curve)



- A perfect classifier: at the upper left corner (only the true positives, no false positives & no false negatives)

PR Curve

- PR curve: Precision vs Recall
  - Precision as Y axis
  - Recall as X axis
- Goal: select an algorithm at the upper right corner



Class Imbalance Problem

- The total # of a class of data (positive): far less than the total # of another (negative)
- Example
  - Model 1: 7 out of 10 cracks and 10 out of 10000 normal pavement pixels WRONG
  - Model 2: 2 out of 10 cracks and 100 out of 10000 normal pavement pixels WRONG
- If the classifier's performance is determined by the number of mistakes,
    - Model 1 (17 mistakes) VS. Model 2 (102 mistakes)

PR Curve Vs ROC Curve

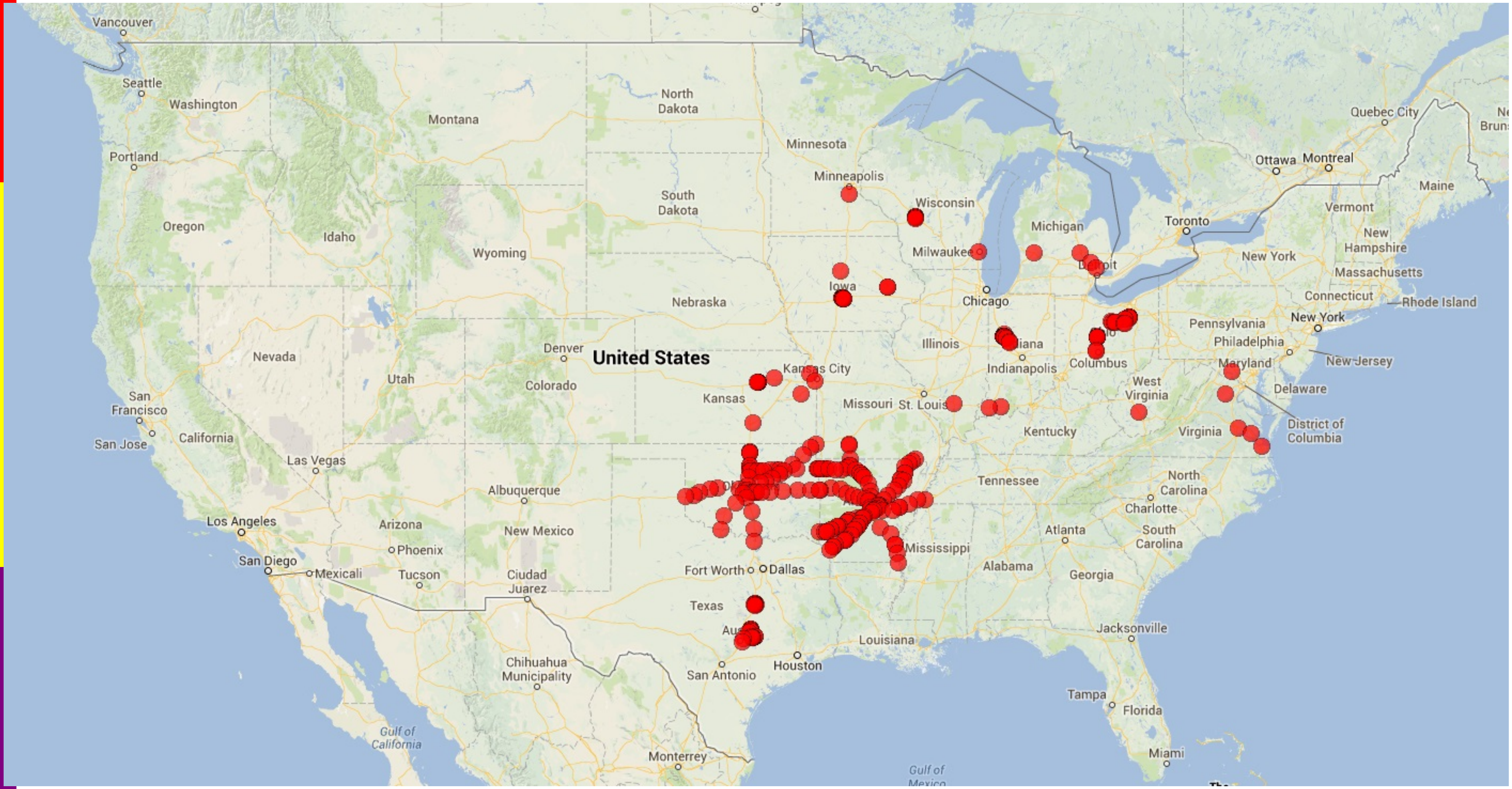
- Imbalance pavement image data set:
  - Distress pixels are far less than normal pixels
- ROC curve uses false positive, which is affected by the number of negative samples

$$tpr = \frac{tp}{tp+fn} \qquad fpr = \frac{fp}{fp+tn}$$

- PR curve focuses on the detection performance of positive samples only

$$\text{Recall} = \frac{tp}{tp+fn} \qquad \text{Precision} = \frac{tp}{tp+fp}$$

Benchmark Image Sources



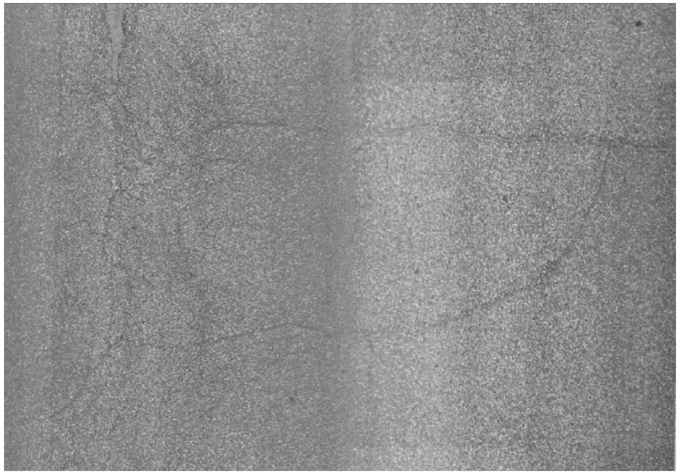
3D Benchmark Image Library

- Total size: 1535
- Image group:
  - Flexible Pavement: 4
  - Rigid Pavement: 4
  - High Friction Surface
- Ground truth generation
  - Crack map images
  - Manual visual inspection

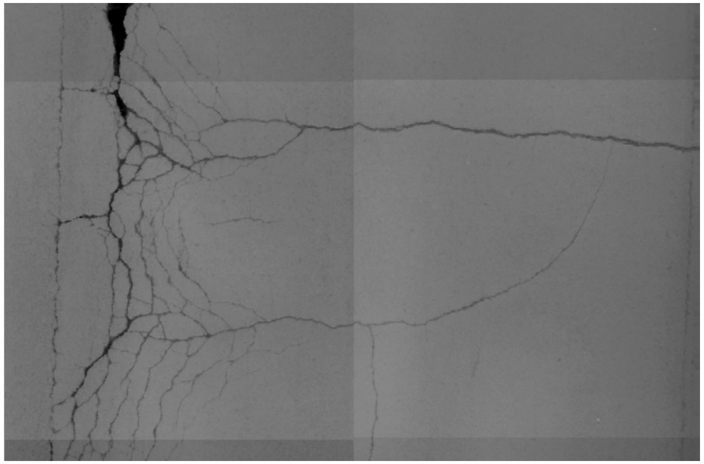
3D Benchmark Image Library

Group	Flexible Pavement				High Friction
	Coarse Surface	Good Quality	Bad Quality	Crack Sealing	
Size	224	255	260	80	61
Group	Rigid Pavement				
	Complex Condition	Good Condition	Texture Pavement	NGCS	
Size	260	285	120	51	

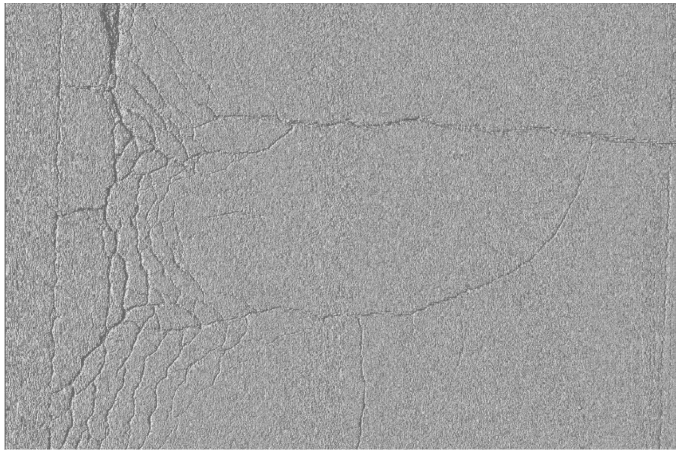
Examples Images



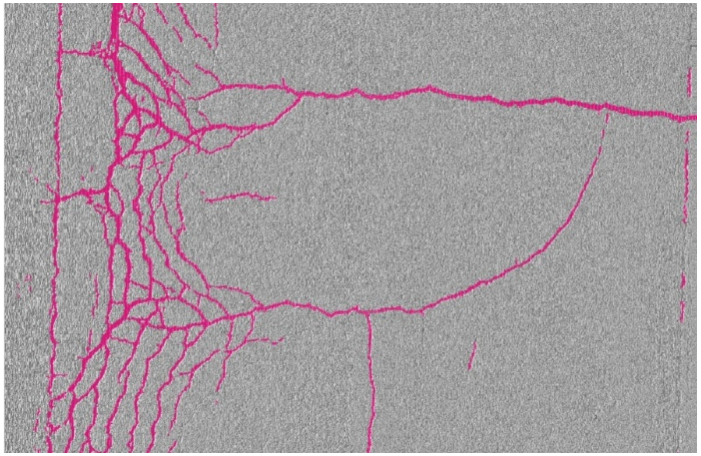
Intensity



3D Range data in grey image format



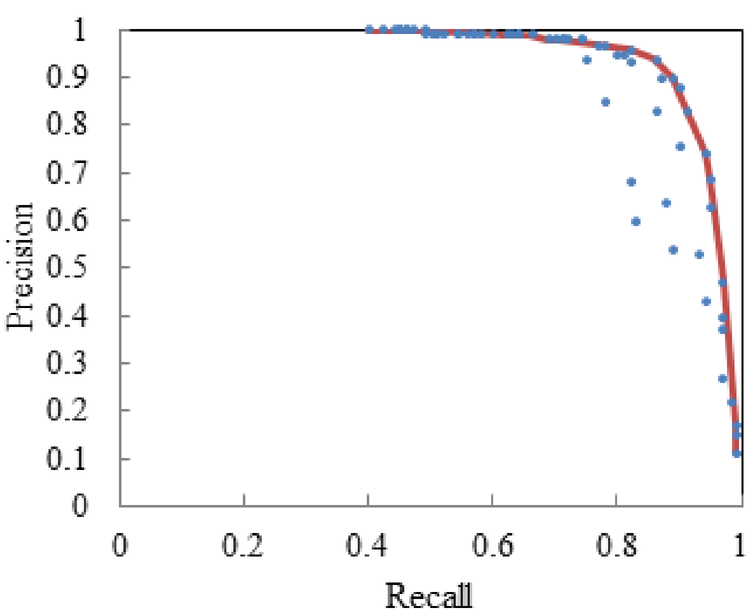
Range data openGL visualization

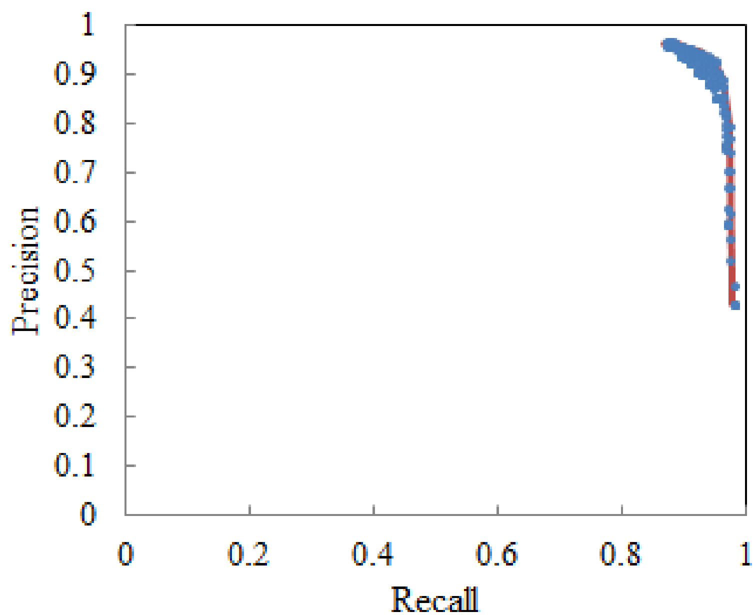


Ground truth manually labeling

Case Studies

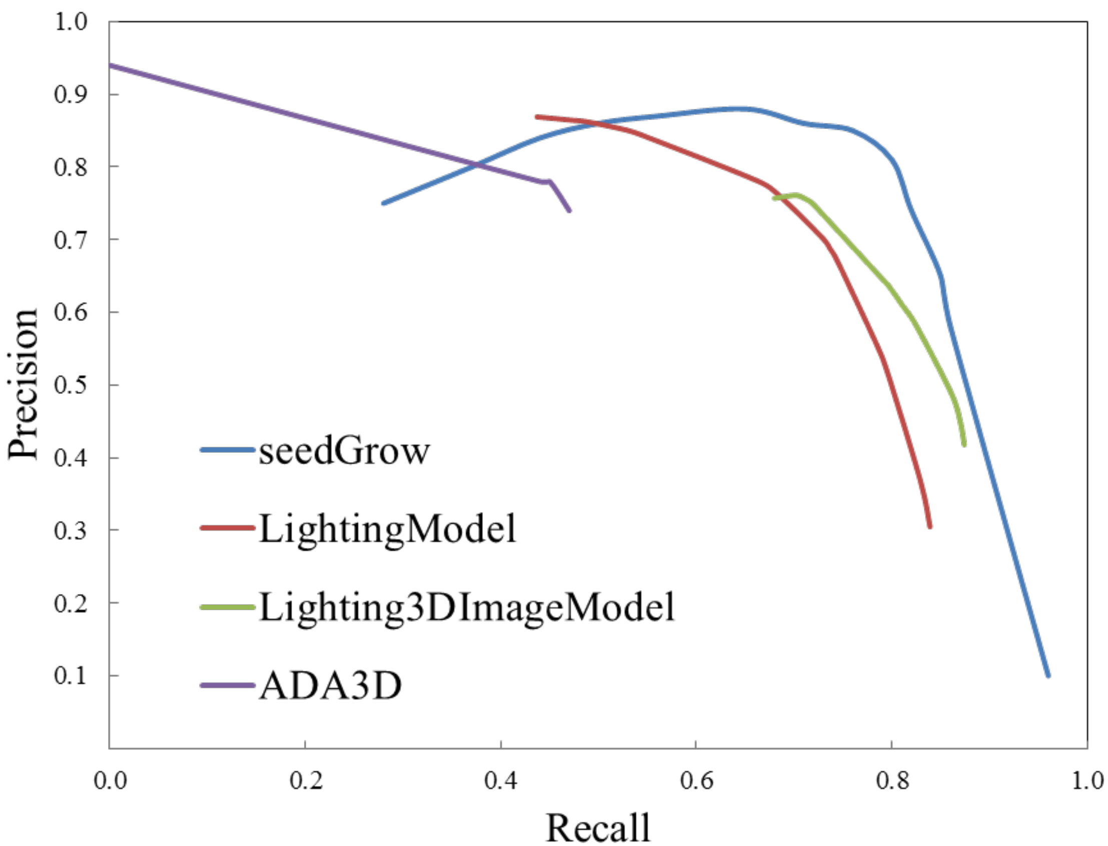
- Performance
- Sensitivity





Performance Analysis

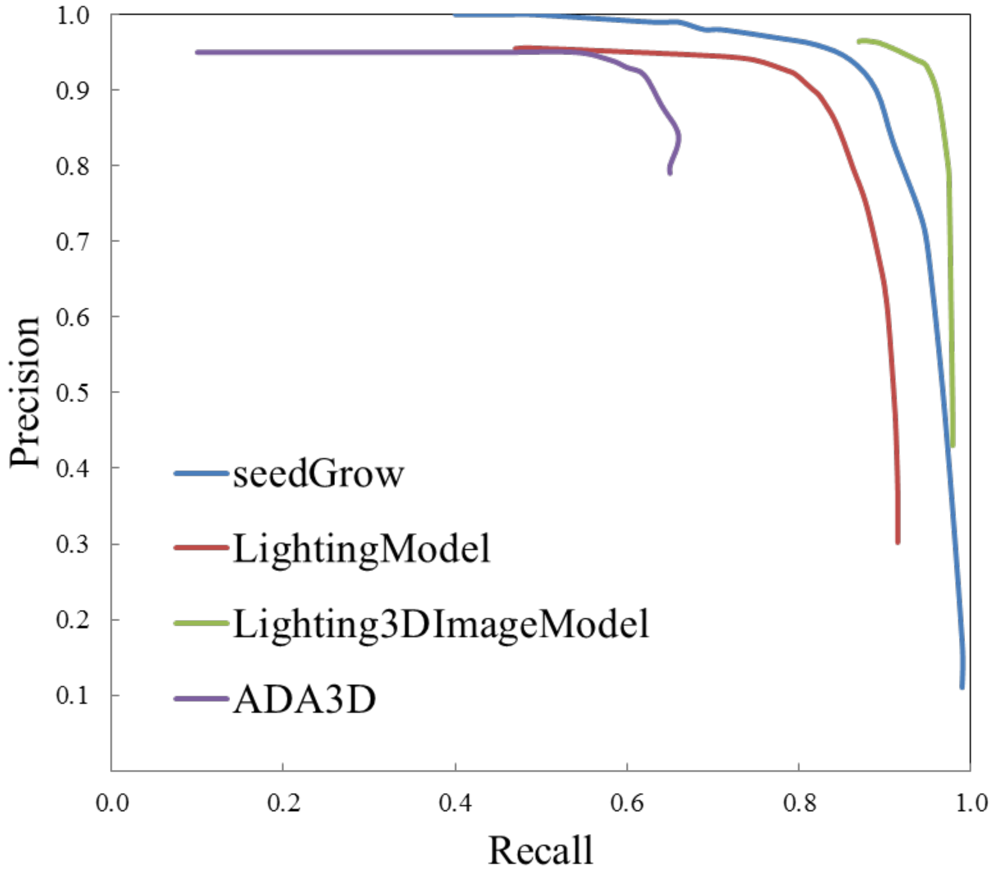
- Asphalt Bad Quality



Test	F-value
SeedGrow	0.80
Lighting Model	0.72
Lighting 3D Image Model	0.73
ADA3D	0.56

Performance Analysis

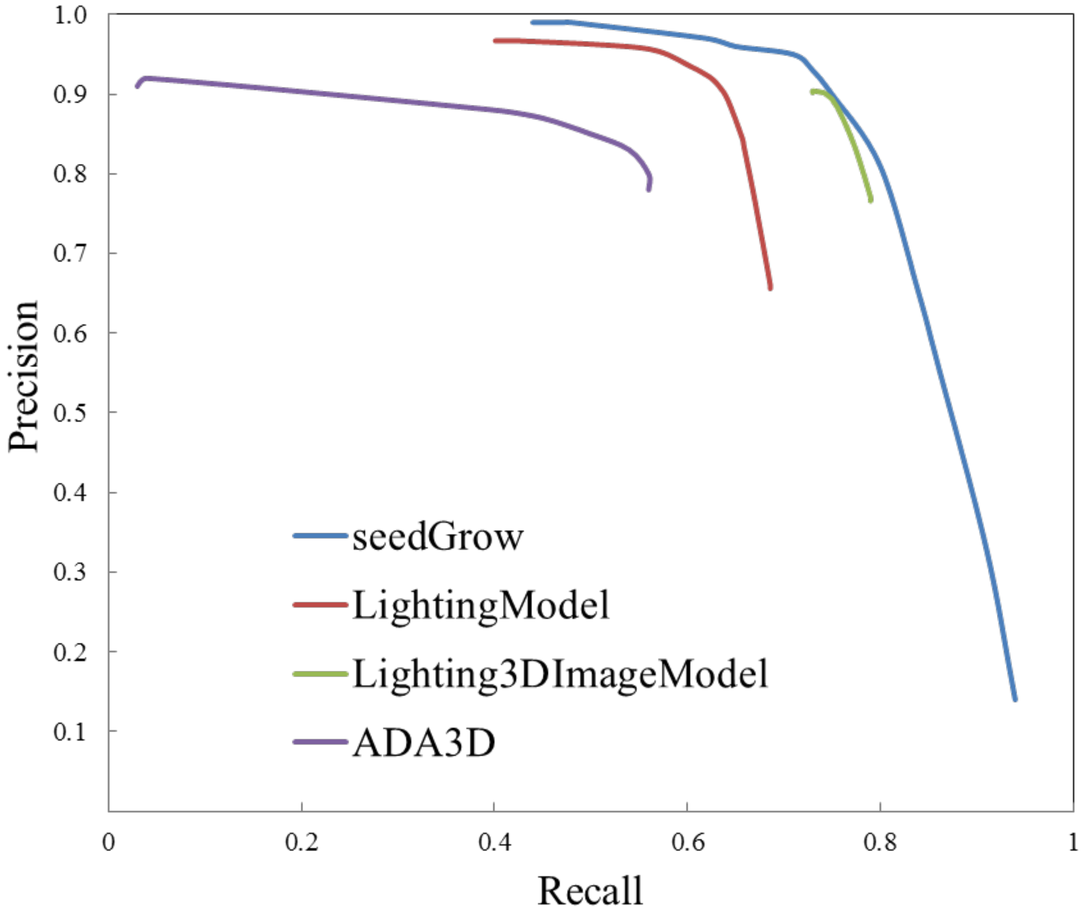
- Asphalt Good Quality



Algorithm	F-value
SeedGrow	0.90
Lighting Model	0.86
Lighting 3D Image Model	0.94
ADA3D	0.74

Performance Analysis

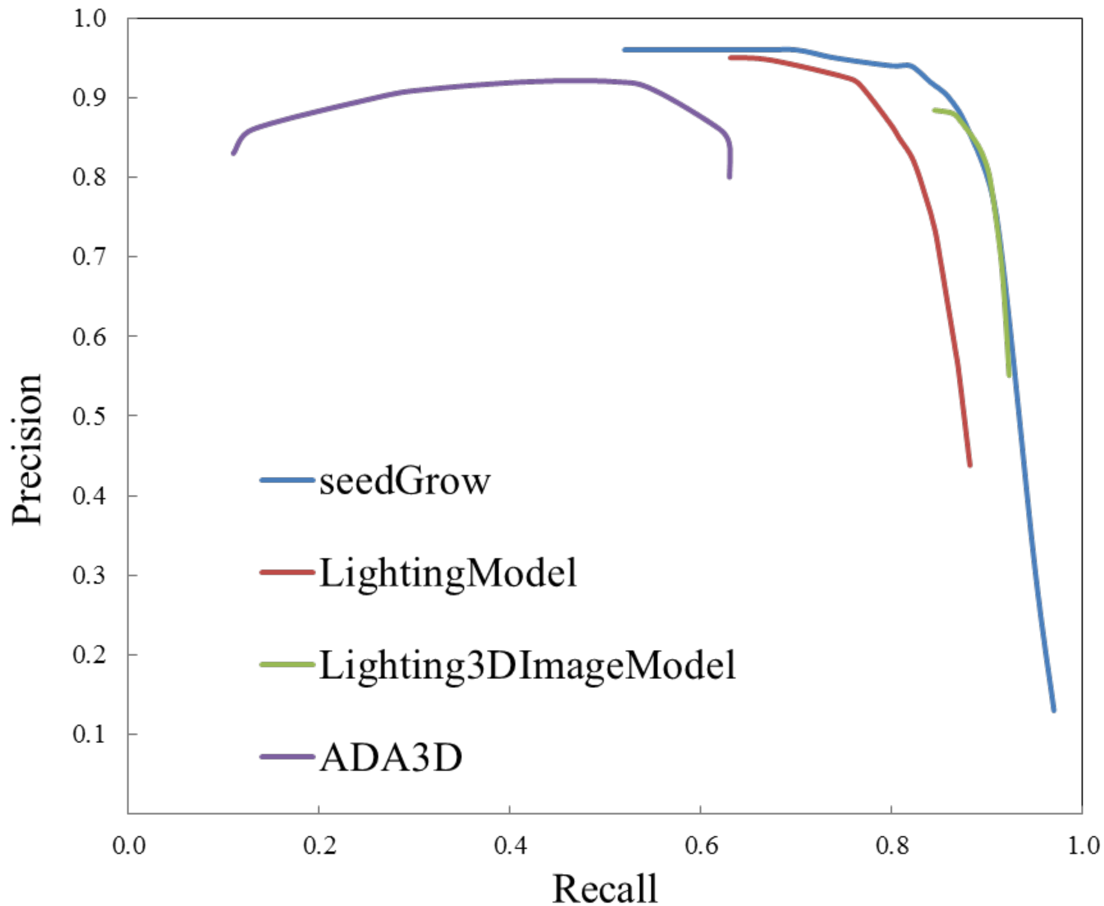
- Concrete Complex Condition



Test	F-value
SeedGrow	0.82
Lighting Model	0.72
Lighting 3D Image Model	0.80
ADA3D	0.66

Performance Analysis

- Concrete Good Condition



Test	F-value
SeedGrow	**0.88**
Lighting Model	0.82
Lighting 3D Image Model	0.86
ADA3D	0.72

Performance Analysis - F score

Test Group	SeedGrow	Lighting Model	Lighting 3D Image Model	ADA3D
Asphalt Bad Quality	**0.80**	0.72	0.73	0.56
Asphalt Good Quality	0.90	0.86	**0.94**	0.74
Concrete Complex Condition	**0.82**	0.72	0.80	0.66
Concrete Good Condition	**0.88**	0.82	0.86	0.72
Average	0.85	0.78	0.83	0.67

SeedGrow > Lighting 3D > Lighting Model > ADA3D

Sensitivity Analysis

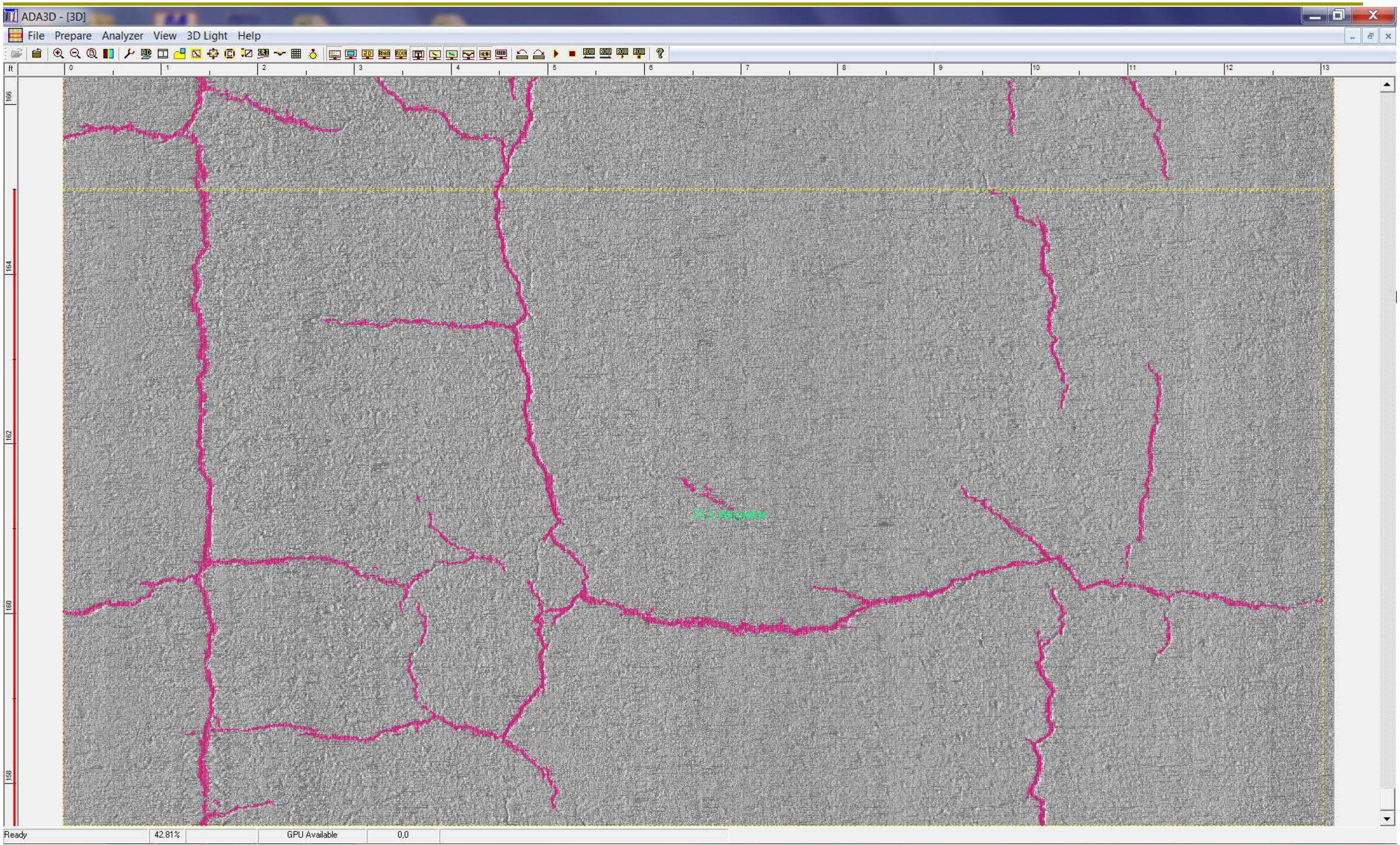
- Calculate SD of discrete PR points from top 40% F score

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{X})^2}{n} + \frac{\sum_{i=1}^{n}(y_i - \bar{Y})^2}{n}}$$

Test Group	SeedGrow	Lighting Model	Lighting 3D Image Model	ADA3D
Asphalt Bad Quality	0.092	0.062	0.015	0.021
Asphalt Good Quality	0.069	0.062	0.020	0.032
Concrete Complex Condition	0.058	0.049	0.008	0.018
Concrete Good Condition	0.053	0.034	0.017	0.020
Average	0.068	0.052	0.015	0.023

Lighting 3D < ADA3D < Lighting Model < SeedGrow

ADA3D Interface



Questions ?

Kelvin C.P. Wang
kelvin.wang@okstate.edu
Oklahoma State University
School of Civil and Environmental Engineering