A Deep-Learning based Fully Automated Cracking Detection with Pixel-Accuracy

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The 10th Int. Conf. on the Bearing Capacity of Road, Railways and Airfields,
June 29 2017, Athens, Greece
Background of Condition
Survey Equipment
Digital Highway Data Vehicle (DHDV, Old Generation)
DHDV with LRIS (# 8, June 2008)
PaveVision3D
PaveVision3D
PaveVision3D
Deployment on TSD
Deployment on TSD
3D Data at 60MPH (100KM/h)
3D Data at 60MPH (100KM/h)
3D Data at 60MPH (100KM/h)
Rail/Tunnel
Automated Inspection, Rail Surface
Multi-Mode Lab at SWJTU
Field Installation of Tunnel3D Sensor
Virtual Tunnel Surface
Field Data Collection, High-Speed Rail
Field Data, Fasterner, High-Speed Rail
Field Data, Fasterner, High-Speed Rail
Broken Rail Tie, 2D
Broken Rail Tie, 3D
Rail Surface & Joint, 3D
Rail Surface Chalk-Mark, 2D
Rail Surface Chalk-Mark, 2D
Rail Surface Chalk-Mark, 3D
Rail Surface Debris, 2D
Rail Surface Debris, 3D
Deep-Learning Progress
Challenges of Cracking Automation

- **Complexity**
  - Pavement Surface: A Highly Complicated Environment with Extensive Uncertainties
  - Distress Identification: Challenging Even for Well-trained Human Operators
  - Diverse Pavement Surface Texture
  - Various Presences of Pavement Distresses
Common Failures

- Inconsistent Accuracies for Pavement with Various Texture

Smooth Pavement Surface

Highly Textured Pavement Surface
Common Failures

- Interference from Other Patterns
Objectives

- Automated Crack Detection
  - Find the Actual Location of Distresses with Pixel-Perfect Accuracy
- Automated Crack Classification
  - Label Distress Types
Deep Learning

- **Strong Learning Ability**
  - Learning from Experiences
  - Exploiting Understanding on New and Unlabeled Examples

- **Versatility**
  - A Deep Learning Network Can Detect Multiple Types of Pavement Distresses

- **Enhanced Reliability**
  - Feed with Exhaustive Variations of Pavement Distresses
Compositional Image Model for Recognition

(Goodfellow et al., *Deep Learning*, 2016)
Convolution Neural Network

- Sharing Weights
- Locally-Connected
- Space-Invariant
- Convolution Layer, Max-Pooling Layer, ReLU Layer, Fully-Connected Layer
- Lack of **Pixel-Perfect Accuracy**
Pixel-Level CNNs

(a) Fundus image  (b) Ground truth  (c) Detected vessels

(d) Proposed Methodology

1. Weakly Annotated Imagenet set
2. Compute CNN features
3. Aggregation Layer
4. Image-level training

1. Test Image
2. Pixel-level labeling

CNN + priors

Feature Extraction
Classifier
Post-processing

Final prediction

P(Building) = 0.30
P(Tree) = 0.82
P(Car) = 0.01

P(Building) = 0.02
P(Tree) = 0.76
P(Car) = 0.20

Input Image
(ortho + dsm + norm_dsm)

Hand-crafted Features

CBF Labeling
CNNs for Cracking Detection

- Images taken by cell phone
- Training Data are limited (500 images)
- Lack of Pixel-Perfect Accuracy

CNNs for Cracking Detection

- Detect Cracks in Image Cells
- Training Data are limited (550 images)
- Lack of Pixel-Perfect Accuracy

*Deep Learning-Based Cracking Damage Detection Using CNNs*, Computer-Aided Civil and Infrastructure Engineering, 2017
Image Library

- **Data Type**
  - 3D Data & 2D Images

- **Image Library Size**
  - 2016-2017: 10,000 3D Images + 10,000 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
Typical Examples in Image Library
CNNs for Cracking Detection, Cell Based

- 11 Layers
- 1,246,496 Parameters
Training

- Recognition Accuracy > 96%

<table>
<thead>
<tr>
<th># of Samples</th>
<th># of Samples with False-positive Errors</th>
<th># of Samples with False-negative Errors</th>
<th>False-positive Error</th>
<th>False-negative Error</th>
<th>Accuracy</th>
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<tbody>
<tr>
<td>23,296</td>
<td>163</td>
<td>684</td>
<td>0.7%</td>
<td>2.936%</td>
<td>96.364%</td>
</tr>
</tbody>
</table>

Error Curve
Learned Filters

1st Convolution Layer
32@15×15×1

2nd Convolution Layer
64@7×7×32

3rd Convolution Layer
128@3×3×64
Testing
CNNs for Cracking Detection, Pixel Based

- **7 Layers**
- **1,159,561 Parameters**
Performance
Performance
3D Cracking Image Lib for Training
Automated Image Library for Network Training

- Large Image Library
  - 3D Data Only for Labeling
  - Exhaustive Variations of Pavement Distresses
  - Manually Marked Ground-truth
- Very Costly based on Manual Labeling
- Newly Developed Labeling Software
  - Critical for Training Efficiency for Automated Inspection of Pavements, Rail, and Tunnel Inspection
Labeling Automation: Extract Features

ADA3D Detected Cracks

Original 3D Data
Labeling Automation: Extract Features

ADA3D Generated Crack Labels

Randomly Rotated, Translated and Scaled Crack Labels
Labeled Cracks & Pavement Background

Add the Random Depth Information to the Crack Label Map

Choose a Crack Free 3D Data Frame as the Background
Automatically Generated Cracking Labels on Pavement, All inn 3D
Conclusions & Future Work

- Exhaustive Image Library: Critical
  - 3D Pavement Data & 2D Pavement Image
  - Exhaustive Variations of Pavement Distresses
  - Manually and Auto Marked Ground-truth
- Self-taught Learning
  - Unsupervised Learning from Unlabeled Data
  - Progressive Improvements in Real-time Applications
- Real-time Application
  - Parallel Computing to Reduce Processing Time