Performance of Fully Automated 3D Cracking Survey with Pixel Accuracy based on Deep Learning

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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 Objects (e.g. Pavement Distresses)

- Enhanced Reliability
  - Feed with Exhaustive Variations of Examples
Deep Learning Application

- **Self-Driving**
  - Human-Car Language Interaction
  - Environment Perception
  - Traffic Condition Handling

- **Medical**
  - New Drug Toxicity Prediction
  - Lung Cancer Diagnosis

- **Financial**
  - Face-Detection-Based Payment Systems
  - Stock Prediction

- **Games**
  - DeepMind Alpha-Go on Board Game
  - OpenAI Universe on Computer Game
Structure Characteristics of CNN

- Sharing Weights
- Locally-Connected
- Space-Invariant
- Convolution Layer, Max-Pooling Layer, ReLU Layer, Fully-Connected Layer
- Lack of **Pixel-Perfect Accuracy**
CNNs for Cracking Detection (Cell Image)

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

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
Pixel-Level CNN

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

(d) Proposed Methodology
- 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>
</tr>
</thead>
<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
CrackNet for Pixel-Level Accuracy

- 7 Layers
- 1,159,561 Parameters
Performance
CrackNet II

- 10 Layers
- 42,571 Parameters
Advantages of CrackNet II over CrackNet

- Deeper Architecture
  - CrackNet: 5 Layers
  - CrackNet II: 10 Layers

- Enhanced Feature Extraction
  - CrackNet: Handcrafted Features + Learned Features
  - CrackNet II: All Learned Features

- Faster Speed
  - CrackNet II is 5 times faster than CrackNet

- Better Performance
  - Higher Precision (Lower False-Positive Rate)
  - Higher Recall (Lower False-Negative Rate)
CrackNet vs. CrackNet II in Eliminating Noises

3D Pavement Images

CrackNet

CrackNet II
CrackNet vs. CrackNet II in Finding Fine Cracks

3D Pavement Images

CrackNet

CrackNet II
CrackNet-V

- 9 Layers
- 64,113 Parameters

INPUT: 512x256 Image

Output: 512x256 Crack Map
VGG

- 3×3 Filters for Convolution Layers
- Stack of Many 3×3 Convolution Layers
- Improved Time Efficiency with Fewer Parameters
Advantages of CrackNet-V over CrackNet

- Deeper Architecture
  - CrackNet: 5 Layers
  - CrackNet-V: 9 Layers

- Robustness in Detecting Fine Cracks
  - CrackNet-V is able to detect more fine cracks

- Faster Speed
  - CrackNet-V is 4 times faster than CrackNet

- Better Performance
  - Significantly Higher Recall (Lower False-Negative Rate)
Performance of CrackNet-V

3D Pavement Images

CrackNet

CrackNet-V
Recurrent Neural Network (RNN)

- Sequence Learning
  - Perform Predictions Given Specific Sequences

- Implication for Pavement Crack Detection
  - Pavement Crack: A Sequence of Distinctive Pixels with Unique Features
Recurrent Neural Network for Crack Detection

Best CrackNet

Best CrackNet + RNN
Recurrent Neural Network for Crack Detection

Best CrackNet

Best CrackNet + RNN
CrackNet on Rigid Surfaces

Jointed Surface

Grooved Surface
Future Work

- Exhaustive Image Library
  - 3D Pavement Data & 2D Pavement Image
  - All Variations of Pavement Distresses
  - Manually Processed Example Data
  - Artificial Example Data

- Long-term Training & Optimization
  - Network Optimization Using Diversified Data
  - Field Tests

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

- Real-time Application
  - Massively Parallel Computing to Reduce Processing Time