Automated Damage Evaluation for Big Visual Data Collected from Disaster

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My Research Interest

**Vision-based damage detection, classification and localization using drone images**

**Technology**
- Image processing
- Machine learning
- Computer vision
- Big data analysis

**Information for Civil engineering applications**

**Visual data classification for post-disaster images**

**Image recognition**
Motivation of the Research

A large collection of images after disaster

Current visual data classification

Various types, size, contents

Image collection platform

Robotic platform

Smart device

Social media

Crowd sourcing

New visual data classification

Processing

Autonomous image classification

Collapse

Spalling

Computer vision
Objective and Contributions of the Research

Objective

Develop **an image annotation method** through autonomous detection, classification, and evaluation of visual data using **deep convolutional neural network** algorithms.

Contributions

- Successfully implement deep convolutional neural network for post-disaster images.
- Build a large-scale database for real-world disaster images and their ground-truth annotations intended for computer vision research in this area.
Deep Convolutional Neural Network (CNN)

Object segmentation
Drone navigation
Mitosis detection
Deep Convolutional Neural Network for Image Classification and Object Detection

Preparation of training data

Large number of images in database

Ground-truth labeled image

Manual labeling

- Collapse
- Spalling/Flaking
- School building
- Façade

A process of training a binary classifier

Ground-truth image

Computer CNN features

Positive

Negative

Corresponding label
Post-Event Reconnaissance Image Database

### Image Resource (83,983 images)

- **Dhub**: 49%
- **EERI**: 31%
- **FEMA**: 7%
- **ETC**: 13%

### Types of Disaster (83,983 images)

- **Earthquake**: 83%
- **Hurricane**: 9%
- **Tornado**: 8%

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**Haiti earthquake in 2010 (3,439 images)**

**L’Aquila (Italy) earthquake in 2009 (414 images)**

**Florida hurricanes in 2004 (1,178 images)**

**Nepal earthquake in 2015 (10,490 images)**
Demonstration of the Techniques: Collapse Classification and Spalling Detection

Collapse

Instance of a structure falling down or in.

Spalling

Break off in fragments
Ground Truth Annotation of Collapse and Spalling

**Collapse**

- Image showing that the buildings or building components
  - lost their original shapes
  - produce a large amount of debris

**Spalling**

- Image including
  - exposed masonry areas in a wall due to cracking followed by flaking
  - exposed rebar in a columns
  - small section lose due to large cracking in a concrete wall
<table>
<thead>
<tr>
<th>Configuration of Training and Testing (Collapse Classification)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CNN architecture</strong></td>
</tr>
<tr>
<td><strong>CNN framework (library)</strong></td>
</tr>
<tr>
<td># of images with/without collapsing damage</td>
</tr>
<tr>
<td>Ratio of training, validation and testing</td>
</tr>
<tr>
<td># of images in a batch size</td>
</tr>
<tr>
<td>Training time (collapsing detection)</td>
</tr>
</tbody>
</table>

**Positive**
- Collapse building
- Damage on a building
- Irrelevant images

**Negative**
- Undamaged building
Samples of Images with the Predicted Classes

<table>
<thead>
<tr>
<th>True-positive: 90.26%</th>
</tr>
</thead>
<tbody>
<tr>
<td>True-negative: 92.16%</td>
</tr>
<tr>
<td>Precision : 0.862 (TP/(TP+FP))</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>417</td>
<td>45</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>FP</th>
<th>TN</th>
</tr>
</thead>
<tbody>
<tr>
<td>67</td>
<td>788</td>
</tr>
</tbody>
</table>
# Configuration of Training and Testing (Spalling Detection)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CNN architecture</strong></td>
<td>Alexnet for binary classification</td>
</tr>
<tr>
<td># of images with spalling/ of spallings</td>
<td>1,086 images having 3,158 spalling</td>
</tr>
<tr>
<td>Ratio of training, validation and testing</td>
<td>0.75 (0.7/0.3), and 0.25 (815 / 271 images)</td>
</tr>
<tr>
<td># of object proposals in each image</td>
<td>2,000 ~ 4,000 (on 512 px)</td>
</tr>
<tr>
<td># of test images (# of spalling's for testing)</td>
<td>217 (814)</td>
</tr>
<tr>
<td>A total number of object proposals</td>
<td>65,652/2,075,453 (pos/neg) for training</td>
</tr>
<tr>
<td>Intersection-over-union (IoU) for positive proposals</td>
<td>0.3</td>
</tr>
<tr>
<td>Batch division for spalling detection</td>
<td>0.3/0.7 (positive/negative)</td>
</tr>
<tr>
<td># of images in a batch size</td>
<td>512</td>
</tr>
<tr>
<td>Training time (spalling detection)</td>
<td>6 hours/epoch (20 epoch) using 1 gpu</td>
</tr>
</tbody>
</table>

![Images of positive spalling](image1.png) ![Images of negative spalling](image2.png)
Samples of Spalling Detection

Object proposals
59.39% of true-positive (9,772/16,454 object proposals)
1.7% of false-negative (11,965/687,860 object proposals)

Final detection
40.48% of true-positive (619/1529)
62.16% of detection rate (506/814)
Post-Event Reconnaissance Image Documentation using Automated Classification

How to support field engineers to readily find and analyze images

Sample Report Generated using the Developed Technique

Ecuador Earthquake, 2016
Conclusion

- Automated post-disaster image classification and object detection methods are developed by processing and analyzing big visual data.

- The method is demonstrated on a specific example classification focused on collapse classification and spalling detection.

- However, the general method can be applied to other civil applications that use large-scale visual data. In the future we plan to incorporate and validate a broader array of damage evaluation methods for broader application.
Researchers

• Shirley J. Dyke (Lyles School of Civil Engineering, Purdue University)
• Chungwook Sim (Civil Engineering, University of Nebraska-Lincoln)
• Julio Ramirez (Lyles School of Civil Engineering, Purdue University)
• Benes Bedrich (Computer Graphics Technology, Purdue University)
• Santiago Pujol (Lyles School of Civil Engineering, Purdue University)
• Alana Lund (Lyles School of Civil Engineering, Purdue University)

Data Contributions

• Datacenterhub.org (CrEEDD: Center for Earthquake Engineering and Disaster Data at Purdue)
• EUCentre (Pavia, Italy)
• Instituto de Ingenieria, National Autonomous University of Mexico
• FEMA and EERI

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