Automated Damage Evaluation for Big Visual Data Collected from Disaster

Chul Min Yeum

Postdoctoral Researcher

Lyles School of Civil Engineering, Purdue, United States.

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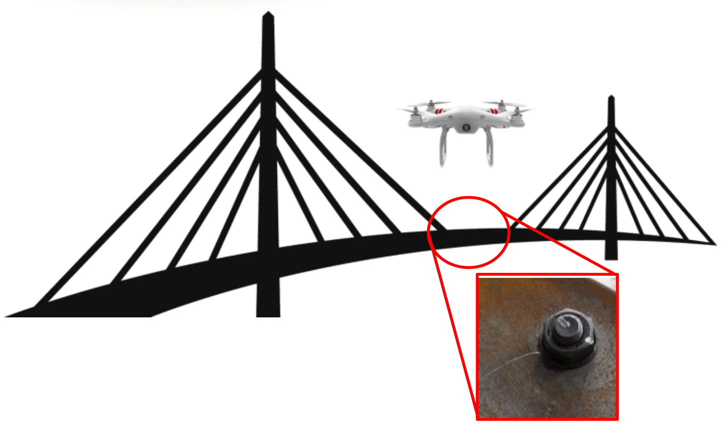
My Research Interest

Technology

Visual data

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

Information for Civil engineering applications



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

Image recognition

Visual data classification for post-disaster images

Motivation of the Research

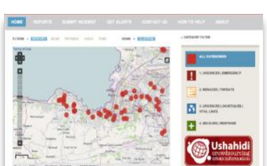
A large collection of images after disaster

Image collection platform

Robotic platform

Smart device

Social media



Crowd sourcing

Current visual data classification

Various types, size, contents

New visual data classification

Processing

Computer vision

Autonomous image classification

Collapse

Spalling

Objective and Contributions of the Research

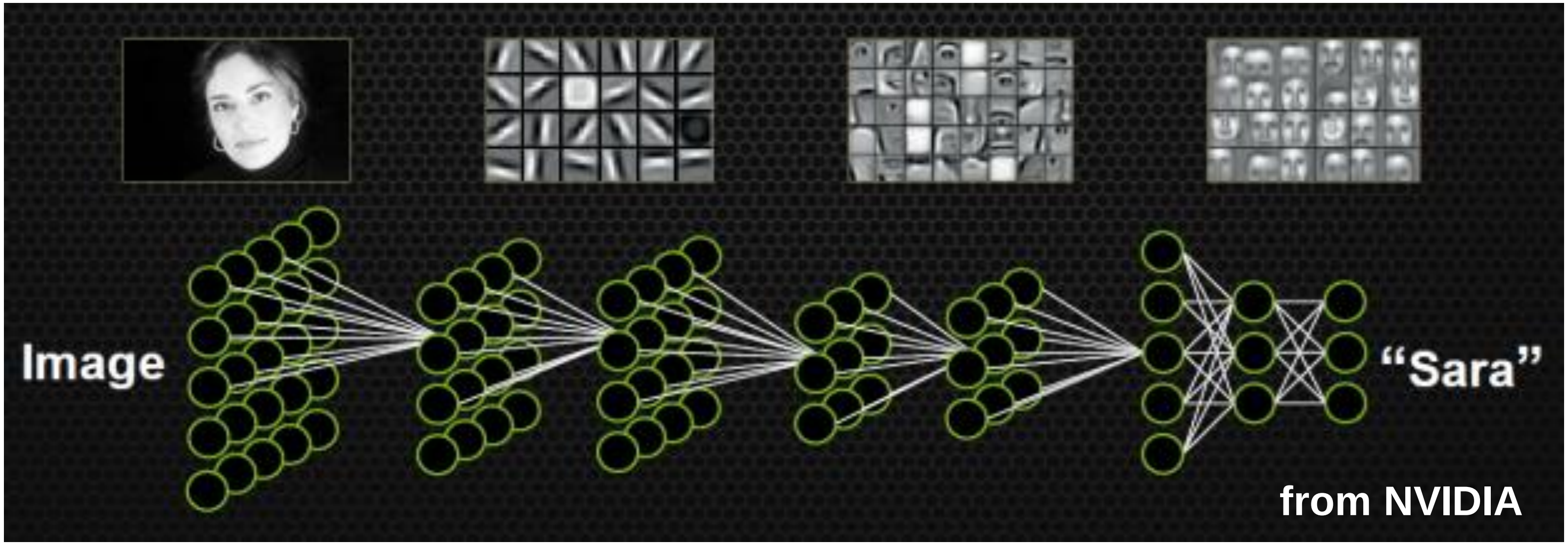
Objective

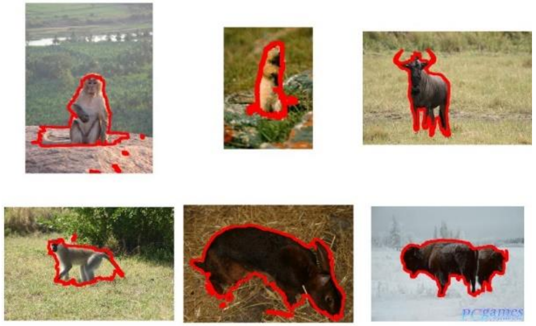
Develop **an image annotation method** through autonomous detection, classification, and evaluation of visual data using **deep convolutional neural network** algorithms.

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.

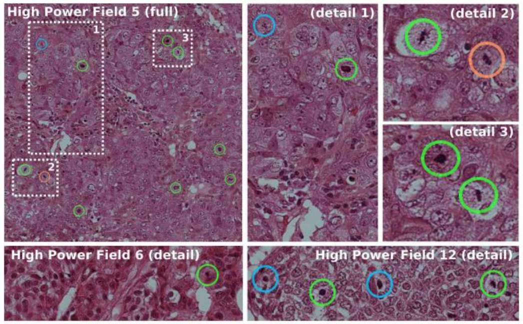
Deep Convolutional Neural Network (CNN)





Object segmentation

Drone navigation

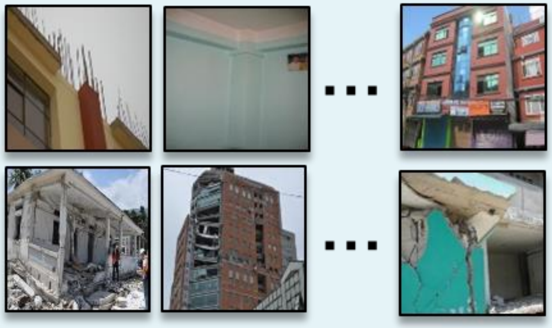


Mitosis detection

Deep Convolutional Neural Network for Image Classification and Object Detection

Preparation of training data

Large number of images in database



Manual labeling

Ground-truth labeled image

Collapse

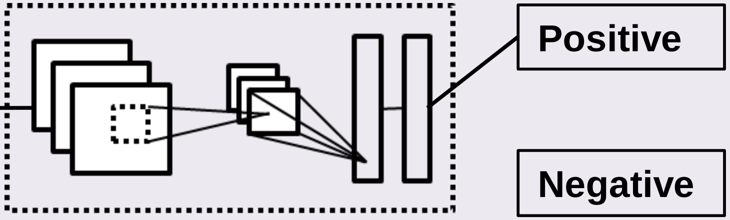
Spalling/Flaking

School building

Façade

A process of training a binary classifier

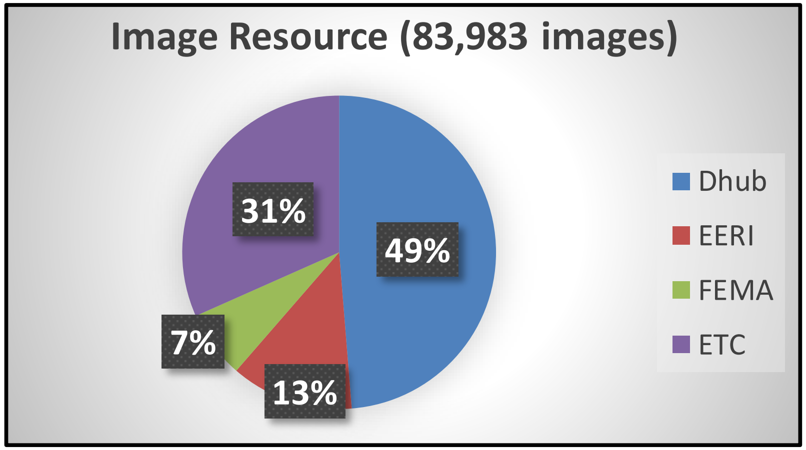
Ground-truth image

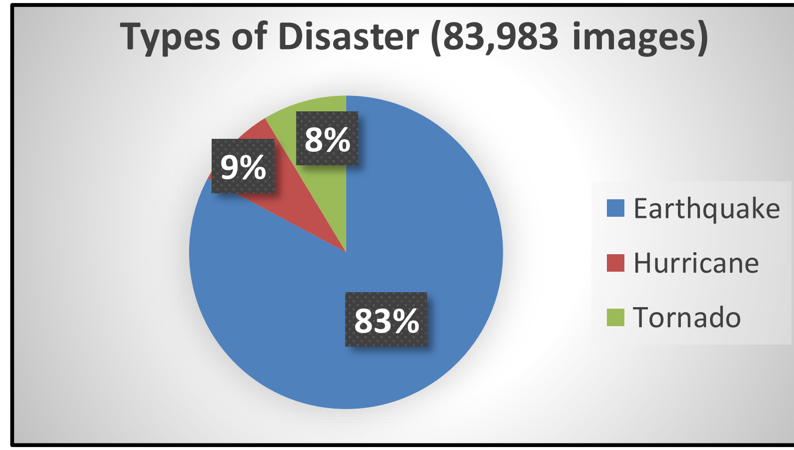


Computer CNN features

Corresponding label

Post-Event Reconnaissance Image Database





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

Configuration of Training and Testing (Collapse Classification)

CNN architecture	: Alexnet for binary classification
CNN framework (library)	: MatCovnet (CNN implementation in Matlab)
# of images with/without collapsing damage	: 1,850/ 3,420 images
Ratio of training, validation and testing	: 0.5, 0.25, and 0.25
# of images in a batch size	: 256
Training time (collapsing detection)	: 0.1 hour/epoch (300 epoch) using 1 GPU

Collapse building

Damage on a building

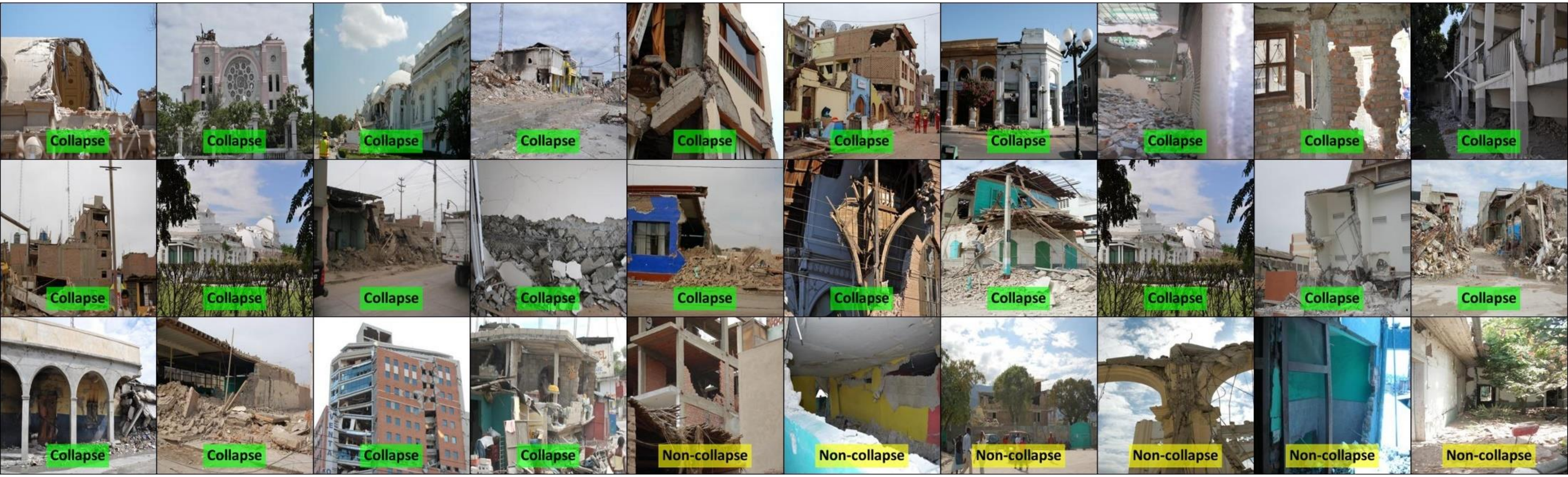
Irrelevant images

Undamaged building

Positive

Negative

Samples of Images with the Predicted Classes

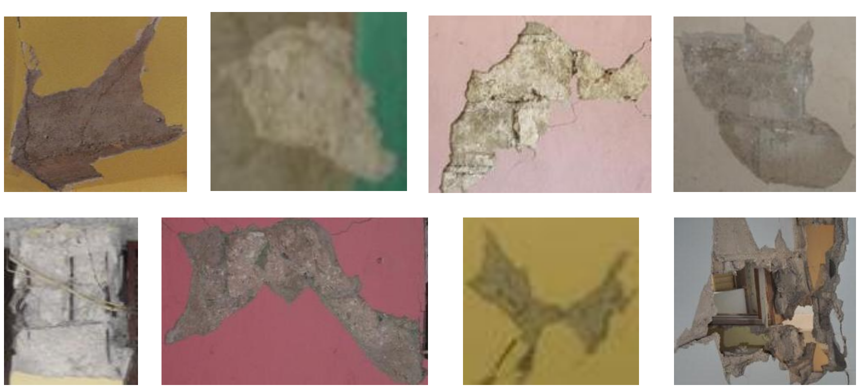


417 (TP)	45 (FN)
67 (FP)	788 (TN)

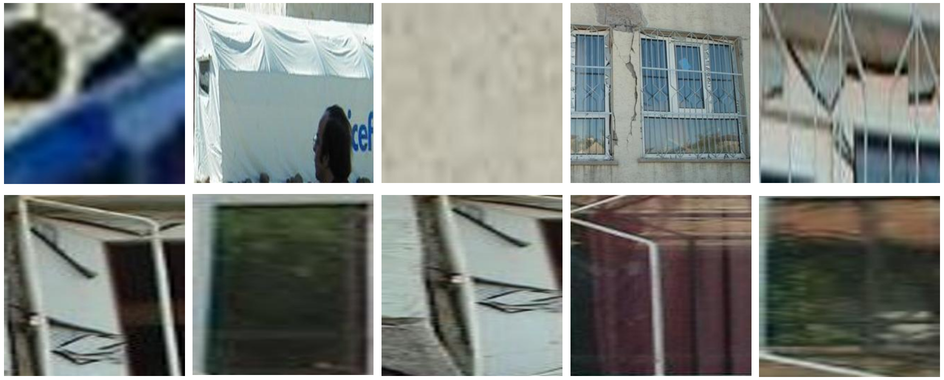
True-positive: 90.26%
True-negative: 92.16%
Precision : 0.862 **(TP/(TP+FP))**

Configuration of Training and Testing (Spalling Detection)

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

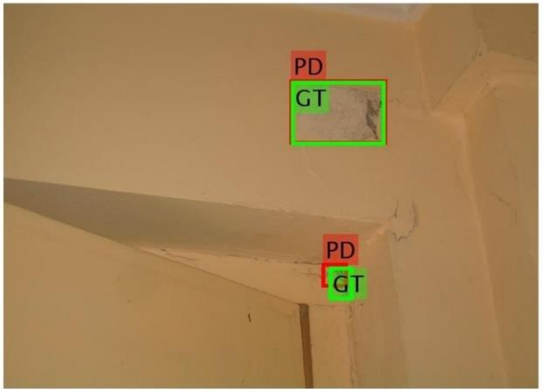


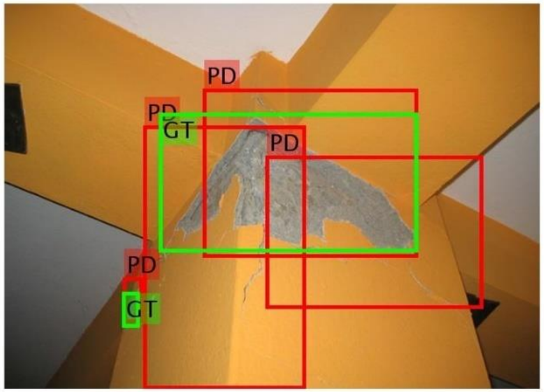
Positive

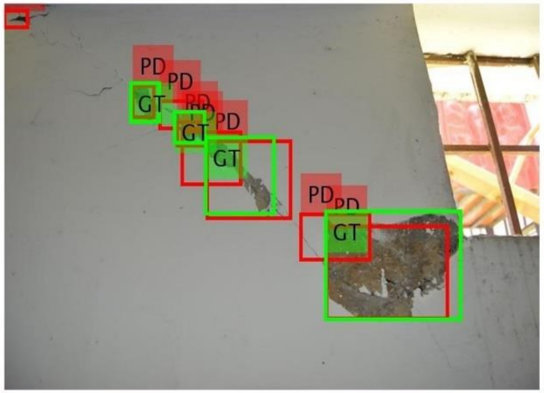


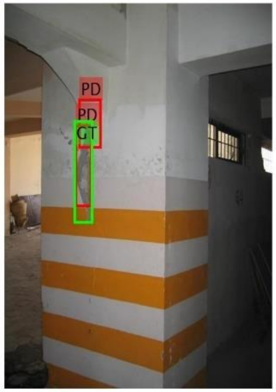
Negative

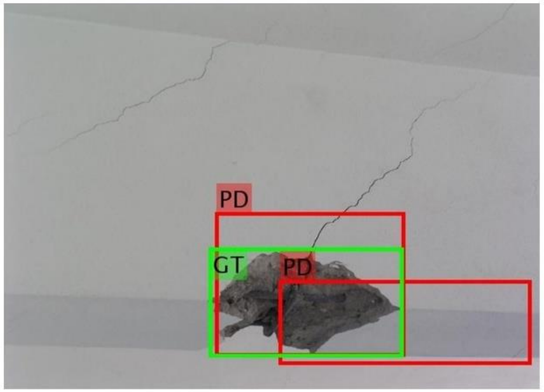
Samples of Spalling Detection

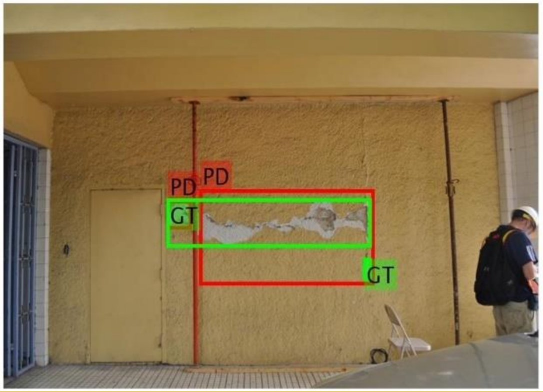












Object proposals

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)

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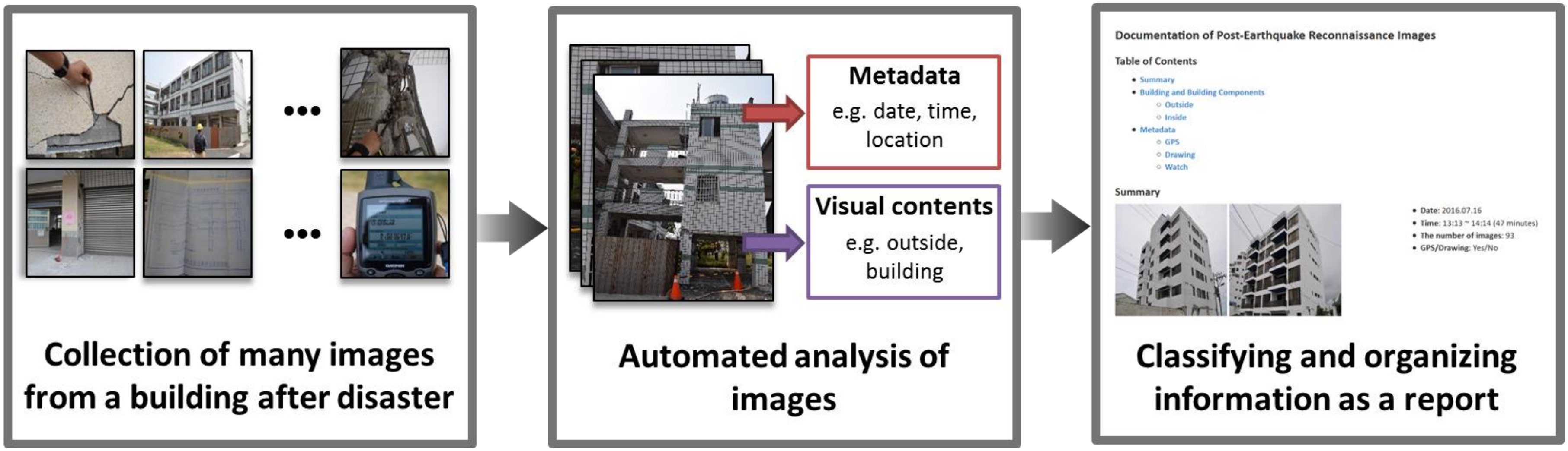
Post-Event Reconnaissance Image Documentation using Automated Classification



How to support field engineers to readily find and analyze images

Chul Min Yeum, Shirley J. Dyke, Benes Bedrich, Thomas Hacker, Julio A. Ramirez, Alana Lund, and Santiago Pujol, "Rapid, Automated Image Classification for Documentation," *submitted to* the 7th Conference on Advances in Experimental Structural Engineering, Pavia, Italy, September 6-8, 2017.

Sample Report Generated using the Developed Technique

Chungwook Sim; Enrique Villalobos; Jhon Paul Smith; Pedro Rojas; Santiago Pujol; Aishwarya Y Puranam; Lucas Laughery (2016), "Performance of Low-rise Reinforced Concrete Buildings in the 2016 Ecuador Earthquake," https://datacenterhub.org/resources/14160.

Sample Report Generated using the Developed Technique (Continue)

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.**

Acknowledgment

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- 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)
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- Instituto de Ingenieria, National Autonomous University of Mexico
- FEMA and EERI

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Questions and Answers