Structured Annotation of Semantic Contents on Images from Earthquake Reconnaissance

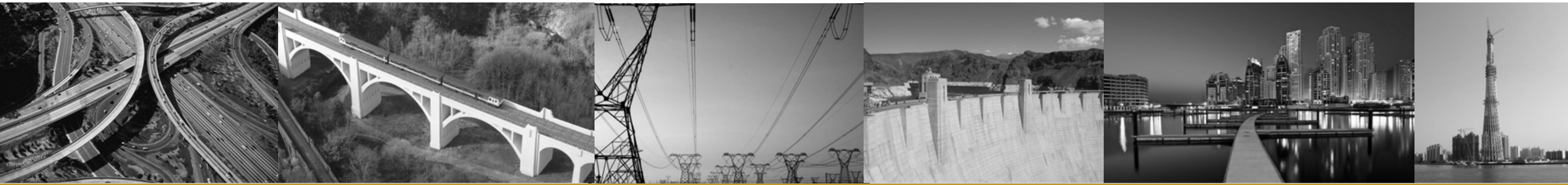
C.M. Yeum[1], S. J. Dyke[2,1], J. Ramirez[1], T. Hacker[3], S. Pujol[1], C. Sim[4]

[1] Lyles School of Civil Engineering, Purdue University, United States

[2] School of Mechanical Engineering, Purdue University, United States

[3] Computer and Information Technology, Purdue University, United States

[4] Civil Engineering, University of Nebraska, United States



Overview of Post-Disaster Damage Evaluation by Incorporating Big Visual Data

A large collection of images from reconnaissance mission

Turkey, 2003

Taiwan, 2016

Nepal, 2015

Ecuador, 2017

Images from at datacenterhub.org

Current visual data classification

Various types, size, contents

New visual data classification

Processing

Computer vision

Autonomous image classification

Collapse

Spalling

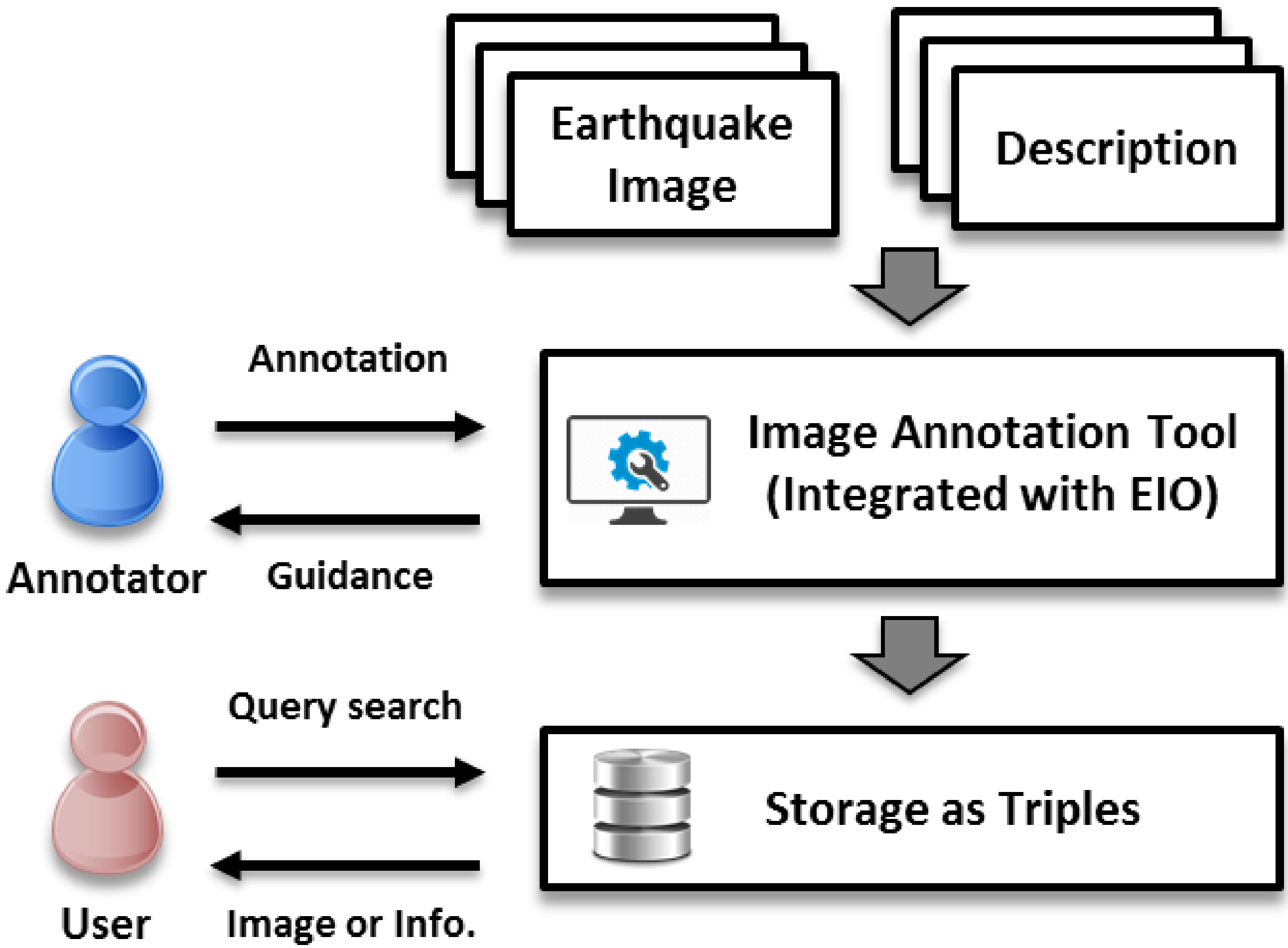
Motivation: How do We Annotate Descriptive Information?

Description

"Reinforced concrete shear wall has longitudinal crushing, spalling at height of the wall, and buckling of vertical reinforcement at the boundary" (Moehle et al., 2011)

- **What should be known to understand the content of the image?**
- **How to annotate such information in a structured way?**

Overview of the Proposed Image Annotation Method



Earthquake Image Ontology

Target **Feature** **Damage** **Object property**

Image Annotation Template

Feature 1   **Target 1**   **(Object property)**   **Feature 2**   **Target 2**

- (F1 and T1), (Object property), and (F2 and T2) represent the subject, verb, and object or adjective, respectively).
- Feature 1 and Feature 2 would contain a class from *Feature* or *Damage*,
- Target 1 and Target 2 would contain a subclass from *Target* or *Damage*
- All fields are not necessarily required in such a statement. However, in each statement, annotators have to enter T1, which is the subject of the statement.

Annotated information in the template is saved as triples.

Annotations of Real-World Earthquake Images

Image 1: Description: Vertical cracks along the Orthogonal Wall (Italy, 1998)
Statements: (F1: *Orthogonal,* T1: *Wall*, F2: *Vertical*, T2: *Cracking*)
Triples: (*Wall – hasDamage – Cracking*), (*Wall – hasShape – Orthogonal*) and (*Cracking – hasDirection – Vertical*)

Image 2: Description: Failure of an unreinforced masonry wall in a building (USA, 1989)
Statements: (F1: *UnreinforcedMasonry,* T1: *Wall*, F2: *Failure*) and (T1: *Wall*, T2: *Building*)
Triples: (*Wall – hasMaterial – UnreinforcedMasonry*), (*Wall – hasDamage – Failure*) and (*Wall – isLocatedAt – Building*)

Image 3: Description: Collapse of a tilt–up bearing wall (1994, Northridge earthquake)
Statements: (F1: *Collapsing*, T1: *TiltWall*)
Triples: *TiltWall – hasDamage – Collapsing*

Annotations of Real-World Earthquake Images (Continue)

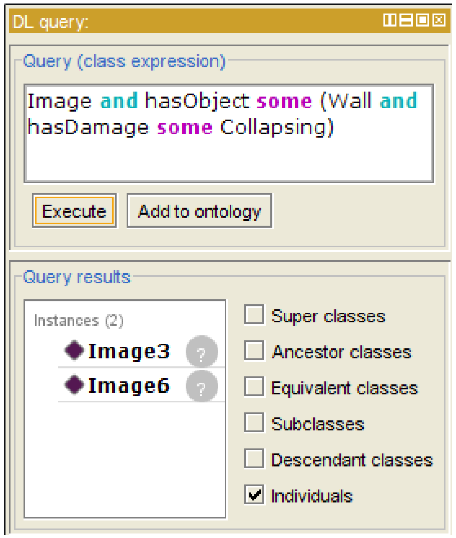
Image 4: Description: Failed captive column in the basement (1999, Turkey earthquake)
Statements: (F1: *Failure*, T1: *CaptiveColumn, T2: Basement*)
Triples: (*CaptiveColumn – hasDamage – Failure*) and (*CaptiveColumn – isLocatesdAt – Basement*)

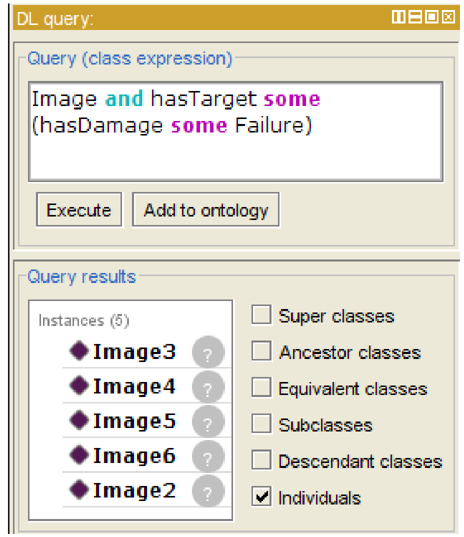
Image 5: Description: Soft story failure (2015, Nepal earthquake)
Statements: (F1: *SoftStory,* T1*: Building*)
Triples: *Building – hasDamage – SoftStory*

Image 6: Description: Shear failure reinforced concrete column next to collapsed masonry wall (2015, Nepal earthquake)
Statements: (F1: *ShearFailure,* T1: *Column,* F2*: Collapsing,* T2*: Wall*) and (F1: *ReinforcedConcrete,* T1: *Column,* F2*: Masonry,* T2*: Wall*)
Triples: (*Column – isLocatedNext – Wall*), (*Column – hasDamage – ShearFailure*), (*Wall – hasDamage – Collapsing*), (*Column – hasMaterial – ReinforcedConcrete*) and (*Wall – hasMaterial – Masonry*)

Evaluation of the Proposed Approach for Image Retrieval

Query 1. Which image has a collapsed wall?
Query 2. Which image has a failure?
Query 3. Which damaged object is located in the basement?





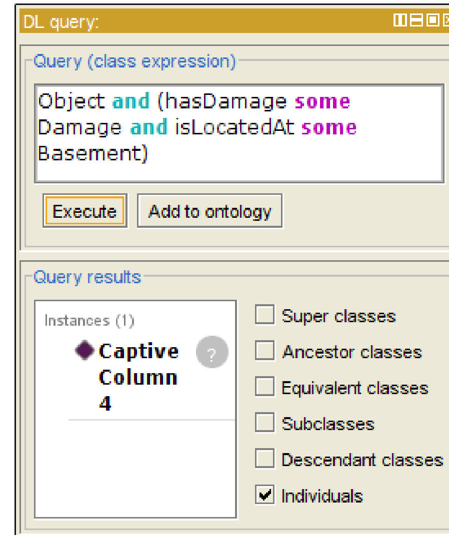


Image 1

Image 2

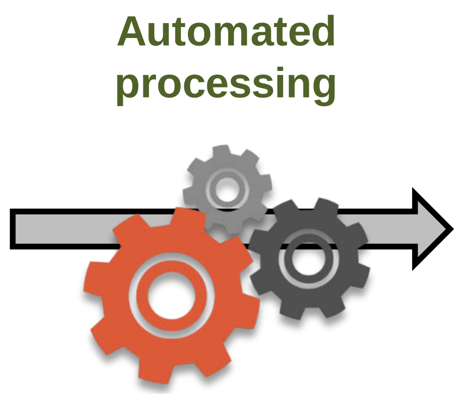
Image 3

Image 4

Image 5

Image 6

What are the Next Step?

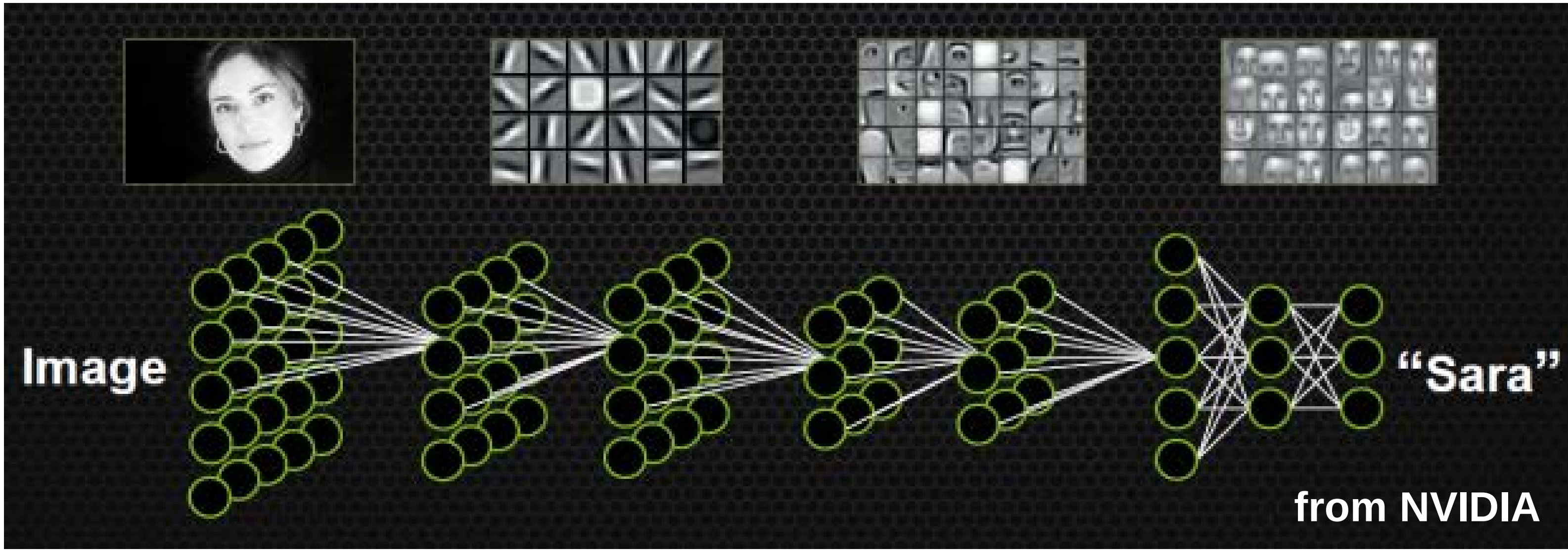


Description

"Reinforced concrete shear wall has longitudinal crushing, spalling at height of the wall, and buckling of vertical reinforcement at the boundary" (Moehle et al., 2011)

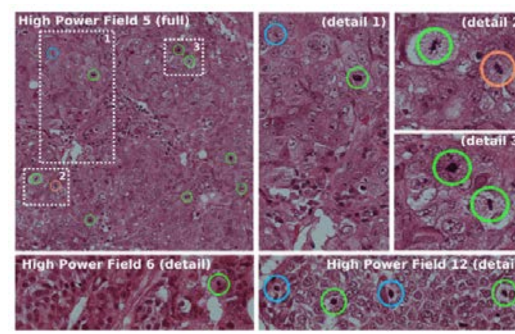
Autonomous detection, classification, and evaluation of visual data that will support scientific research and decision-makring in the filed using **deep convolutional neural network** algorithms.

Deep Convolutional Neural Network (CNN)



Object segmentation

Drone navigation



Mitosis detection

Examples of Image (Scene) Classification and Object Detection

Image Classification

Collapse

Building façade

A Class of an image

Object Detection

Column

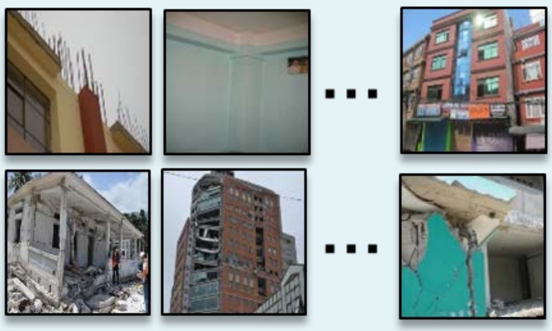
Spalling

Class and location of sub-region within each image

Deep Convolutional Neural Network for Image Classification and Object Detection

Preparation of training data

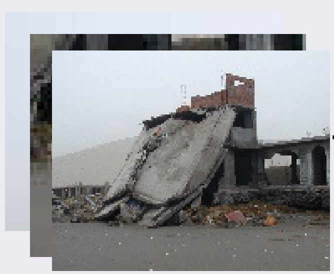
Large number of images in database



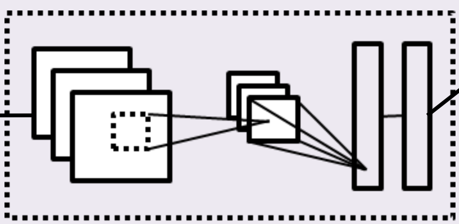
Manual labeling

Ground-truth labeled image

A process of training a binary classifier



Ground-truth image



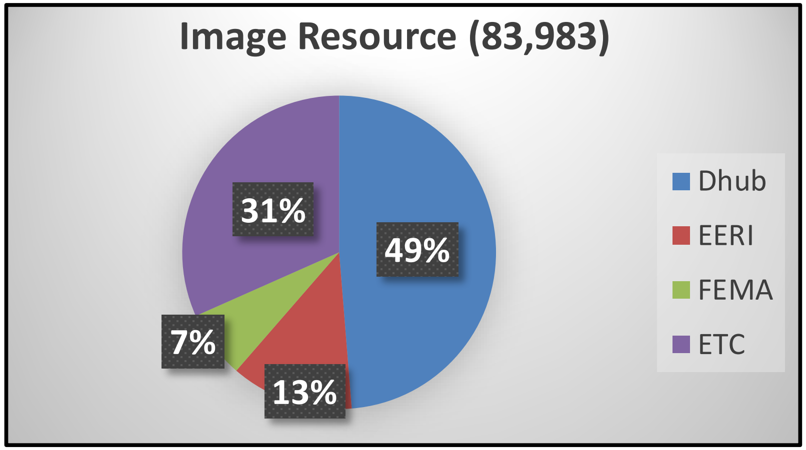
Computer CNN features

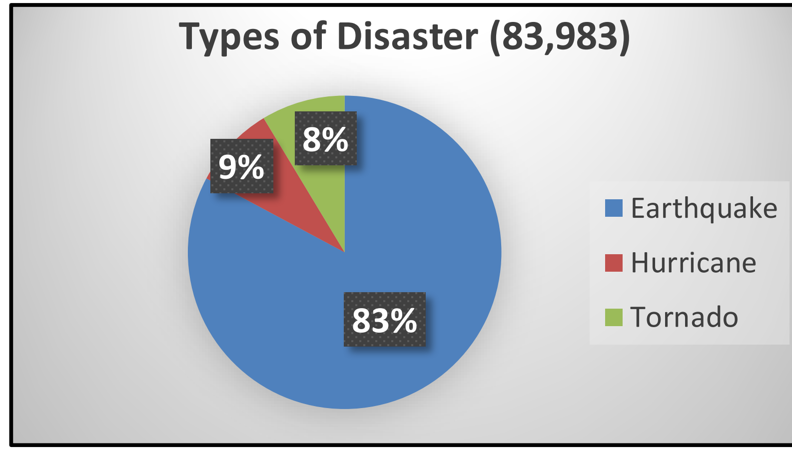
Positive

Negative

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
- are not serviceable or accessible

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

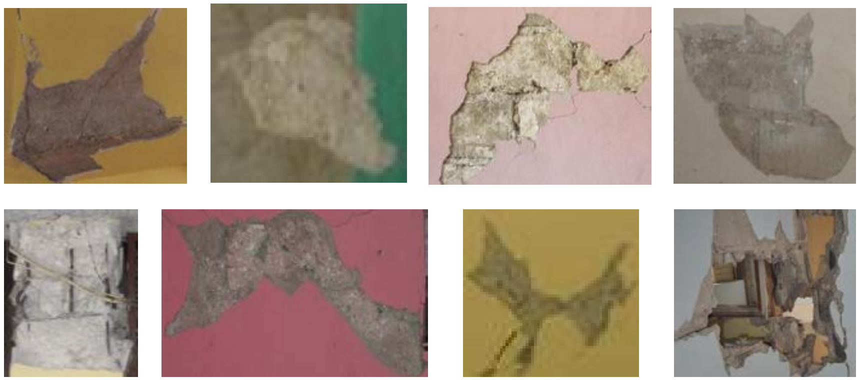
Samples of Images with the Predicted Classes

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)

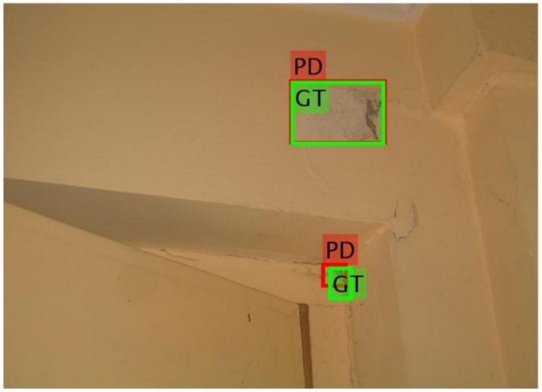
CNN architecture	: Alexnet for binary classification
# of images with spalling/ of spallings	: 1,086 images having 3,158 spalling
Ratio of training, validation and testing	: 0.75 (0.7/0.3), and 0.25 (815 / 271 images)
# of object proposals in each image	: 2,000 ~ 4,000 (on 512 px)
# of test images (# 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

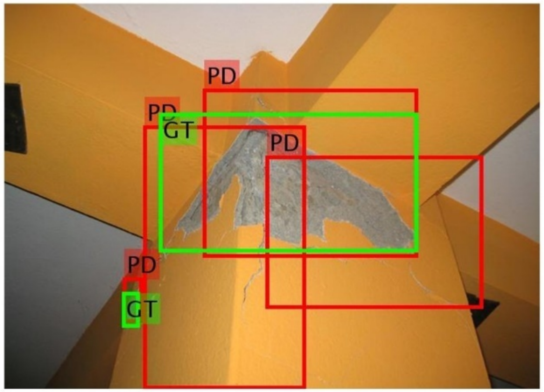


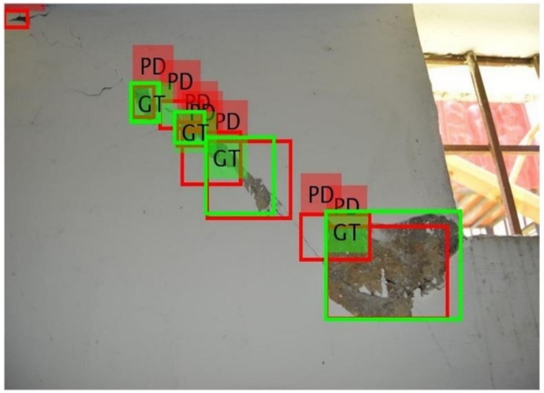
Positive

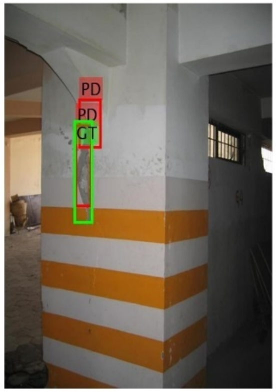
Negative

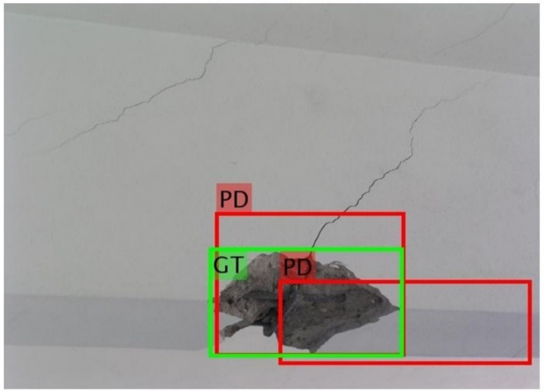
Samples of Spalling Detection

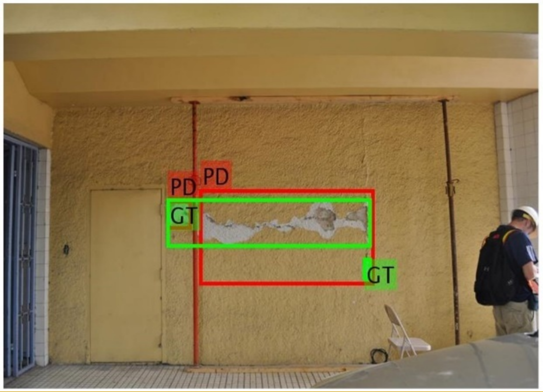












Object proposals

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)

Conclusion

- We propose an ontology and annotation tool that enables documentation and retrieval of visual semantic contents in earthquake images.
- The proposed method can transform the meaning of original descriptions into a searchable form using triples to future retrieval based on visual contents on images.
- This method represents a major step forward toward understanding earthquake images in an automated way by providing quality data for training the deep learning algorithm.

Acknowledgement

- National Science Foundation under Grant No. NSF-CNS-1035748
- CREED (Center for Earthquake Engineering and Disaster Data) at Purdue
- EERI and CEISMIC
- EUCentre (Pavia, Italy),
- Instituto de Ingenieria, UNAM (Mexico)
- FEMA, USA

DATAHUB

FEMA

INSTITUTO DE INGENIERÍA UNAM

CEISMIC Canterbury Earthquake Digital Archive

EUCENTRE™ European Centre for Training and Research in Earthquake Engineering

EERI

Questions and Answers