Computer Vision-based Structure Assessment Exploiting Large Volumes of Images

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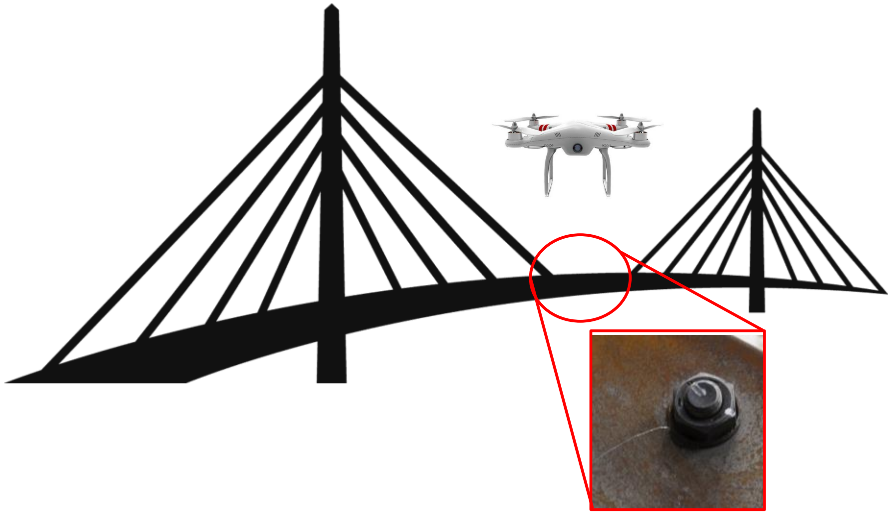
Presentation Outline

1. Introduction
2. Research Topic 1: Autonomous Image Localization (Chapter 3)
3. Research Topic 2: Visual Data Classification in Post-event Building Reconnaissance (Chapter 5)
4. Conclusions

Two Major Research Topics Addressed in the Presentation

- **Image processing**
- **Machine learning**
- **Pattern recognition**
- **Computer vision**
- **Big data**

Civil Engineering Applications



Autonomous image localization (chapters 3)

Image recognition

Visual data classification in post-event building reconnaissance (chapters 5)

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Problems of Current Visual Inspection

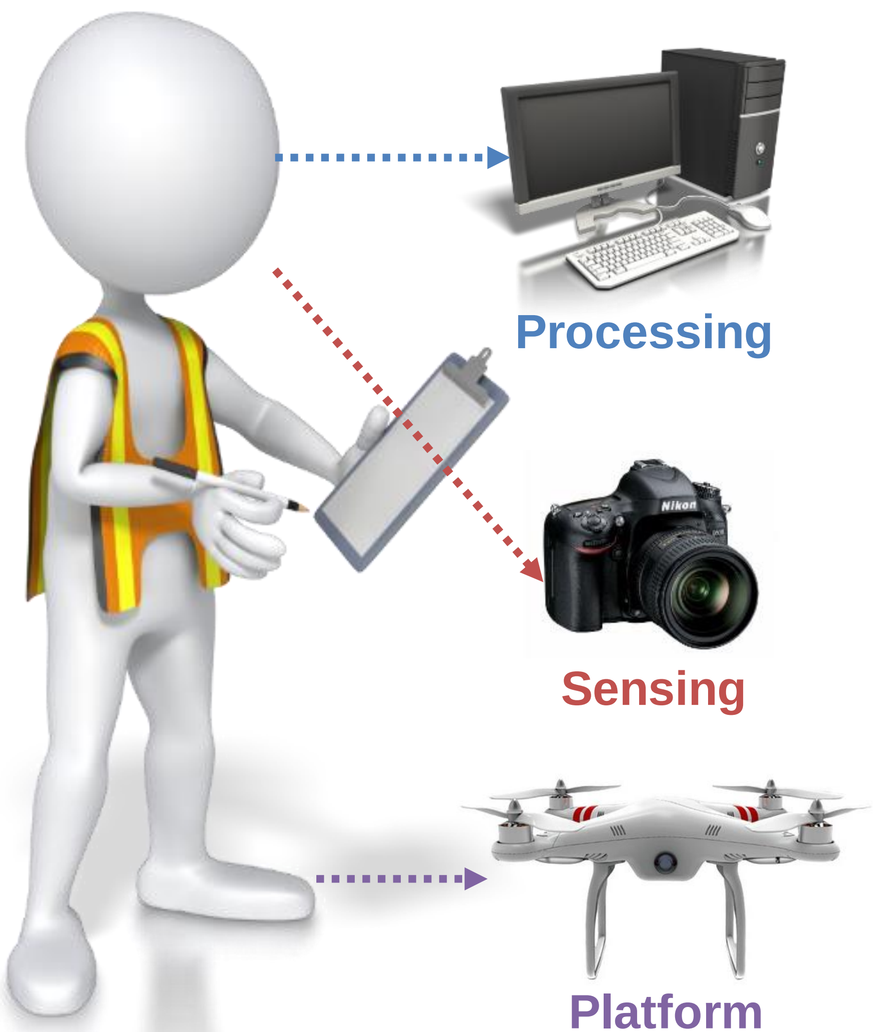
Dangerous works

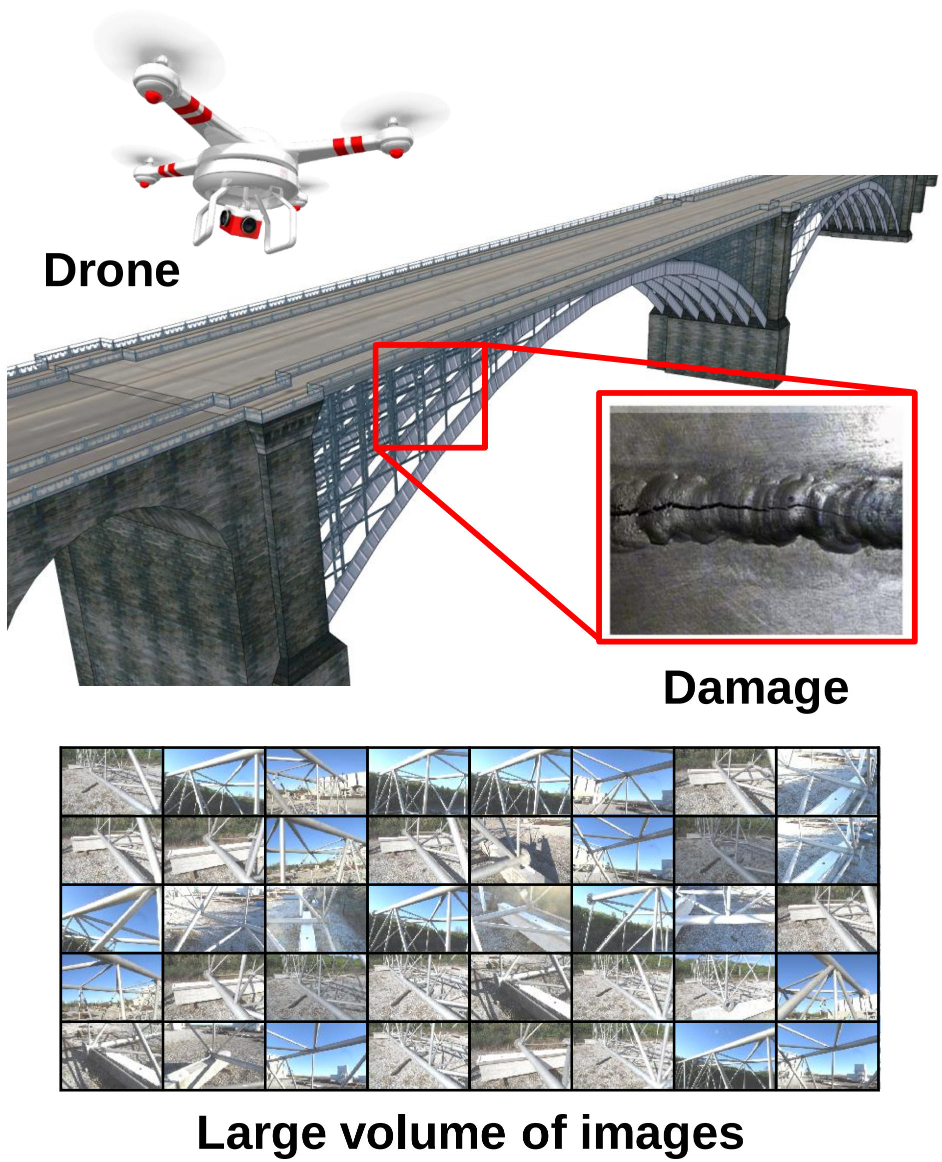
Low accessibility

Traffic block

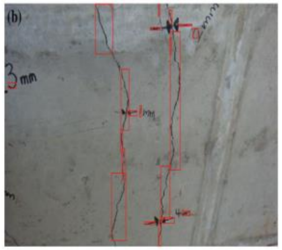
- Large scale
- Subjective interpretation
- Accessibility
- Periodic inspection
- Time consuming

Proposed Approach: Autonomous Visual Inspection





Literature Review



Crack detection and quantification

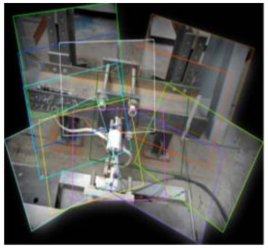
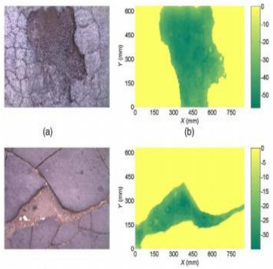
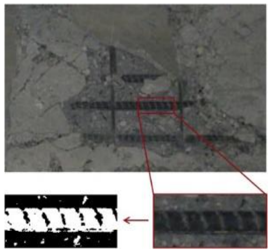


Image stitching for defect detection



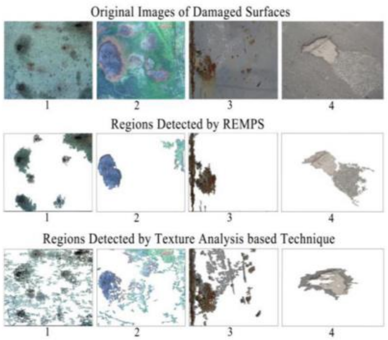
Pavement defect detection and quantification



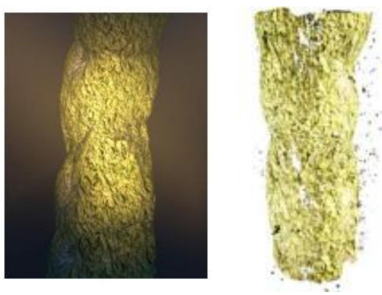
Spalling detection

Post earthquake evaluation

brick counting for façade construction

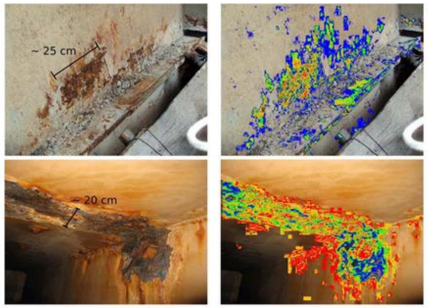


Surface damage segmentation



3D recovery for underwater inspection

Vessel inspection using UAV



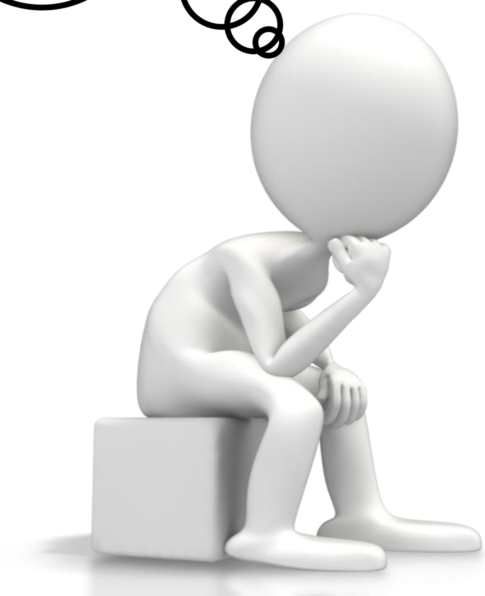
Corrosion detection

1 2 3 4

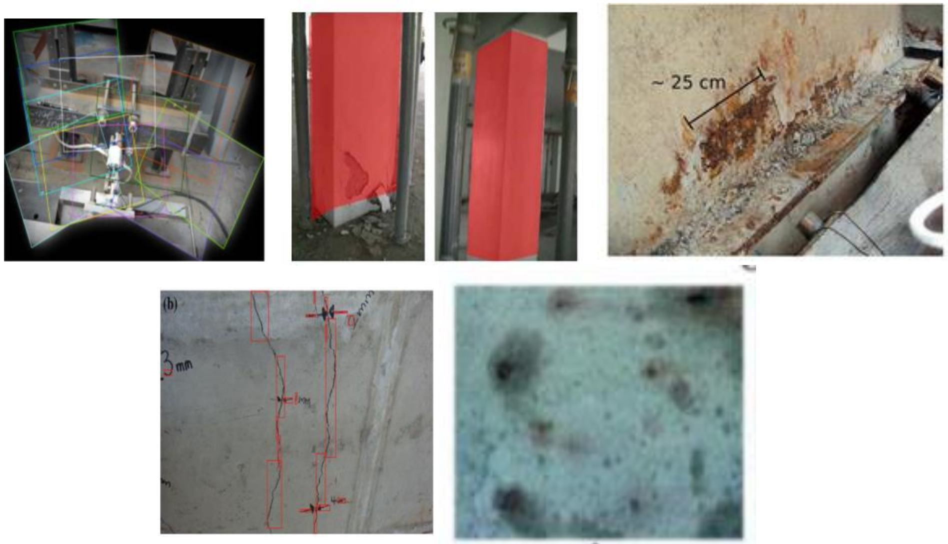
1. Mohammad R Jahanshahi, Purdue University, USA
2. Ioannis Brilakis, Cambridge, UK
3. Michael O'Byrne, Trinity College Dublin, Ireland
4. Alberto Ortiz, University of Balearic Islands, Spain

A Major Gap between Current Research and Practice

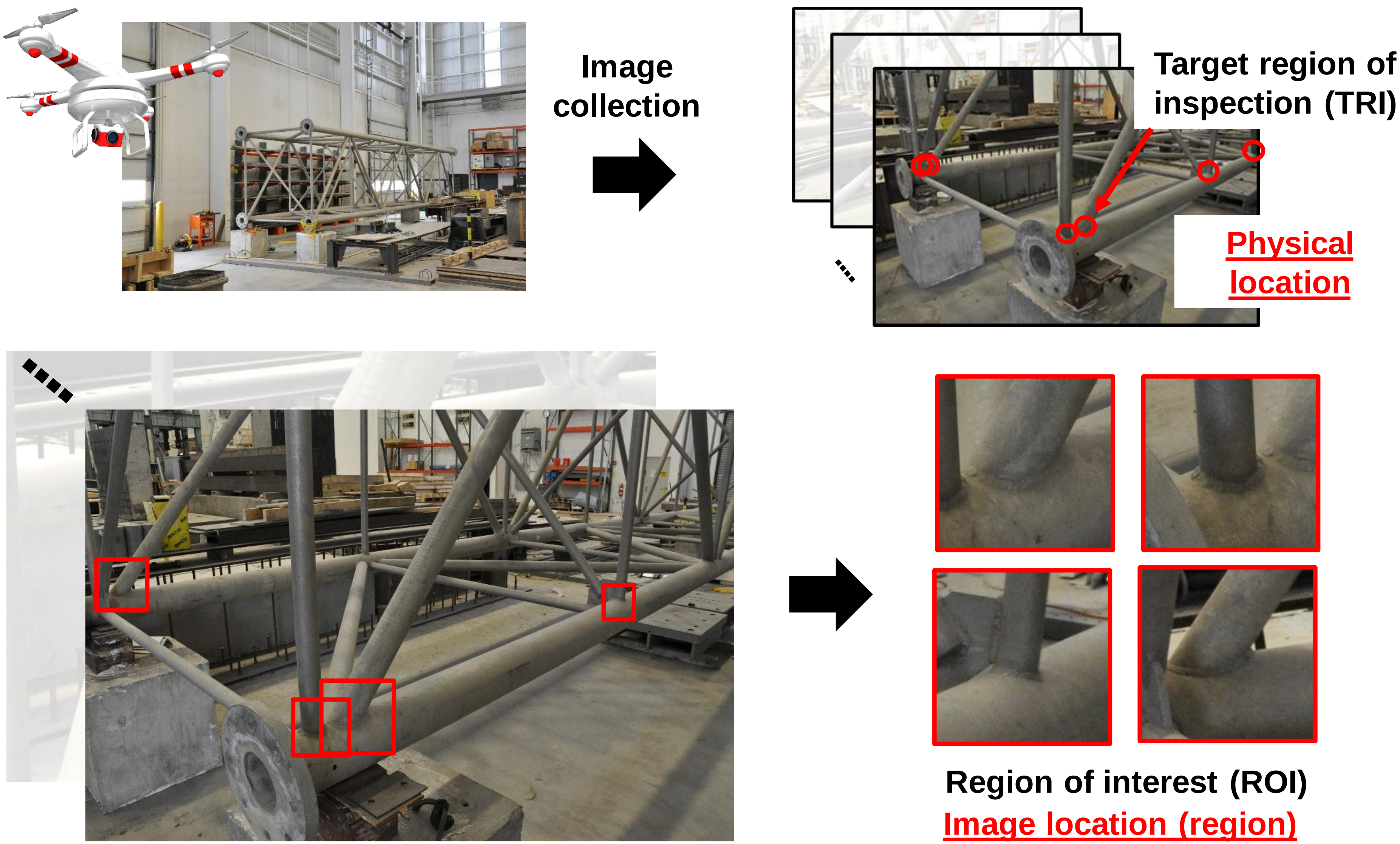
How to extract such favorable images?



A large volume of images collected from drones



Overview of the Developed Technique



Research Topic 1: Objective and Contribution

Objective

Development of an image localization technique that can automatically extract the regions-of-interest (ROI) on each of the collected images so as to process and analyze only highly relevant and localized image areas for visual inspection or damage detection.

Contribution

Development of an enabling technique to facilitate successful application of existing damage detection techniques on large volumes of actual images in an efficient and reliable way. The key is to avoid unnecessary processing of the large portion that are irrelevant and complex.

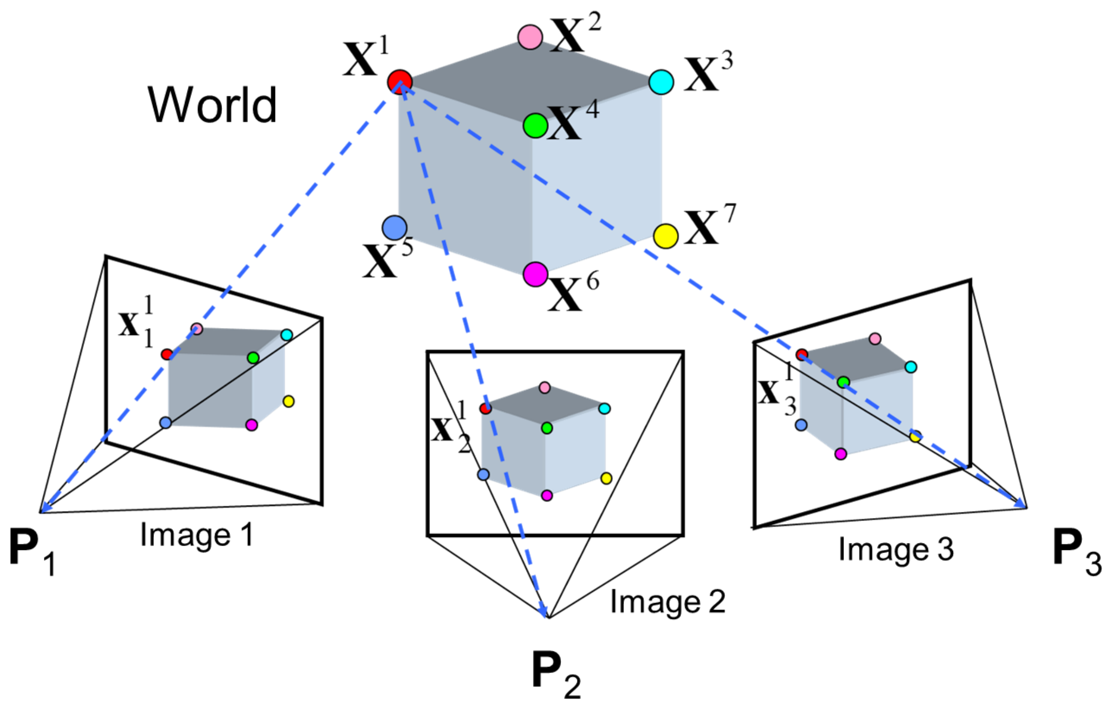
What is Structure from Motion (SfM)?

Pictures

Scene structure & Camera locations and parameters

- **No need for prior camera calibration**
- **No need for prior selection of image locations**
- **No need to capture images using a single camera**

Projection Matrix from Structure from Motion (SfM)



TRI

↓ **Projection matrix**

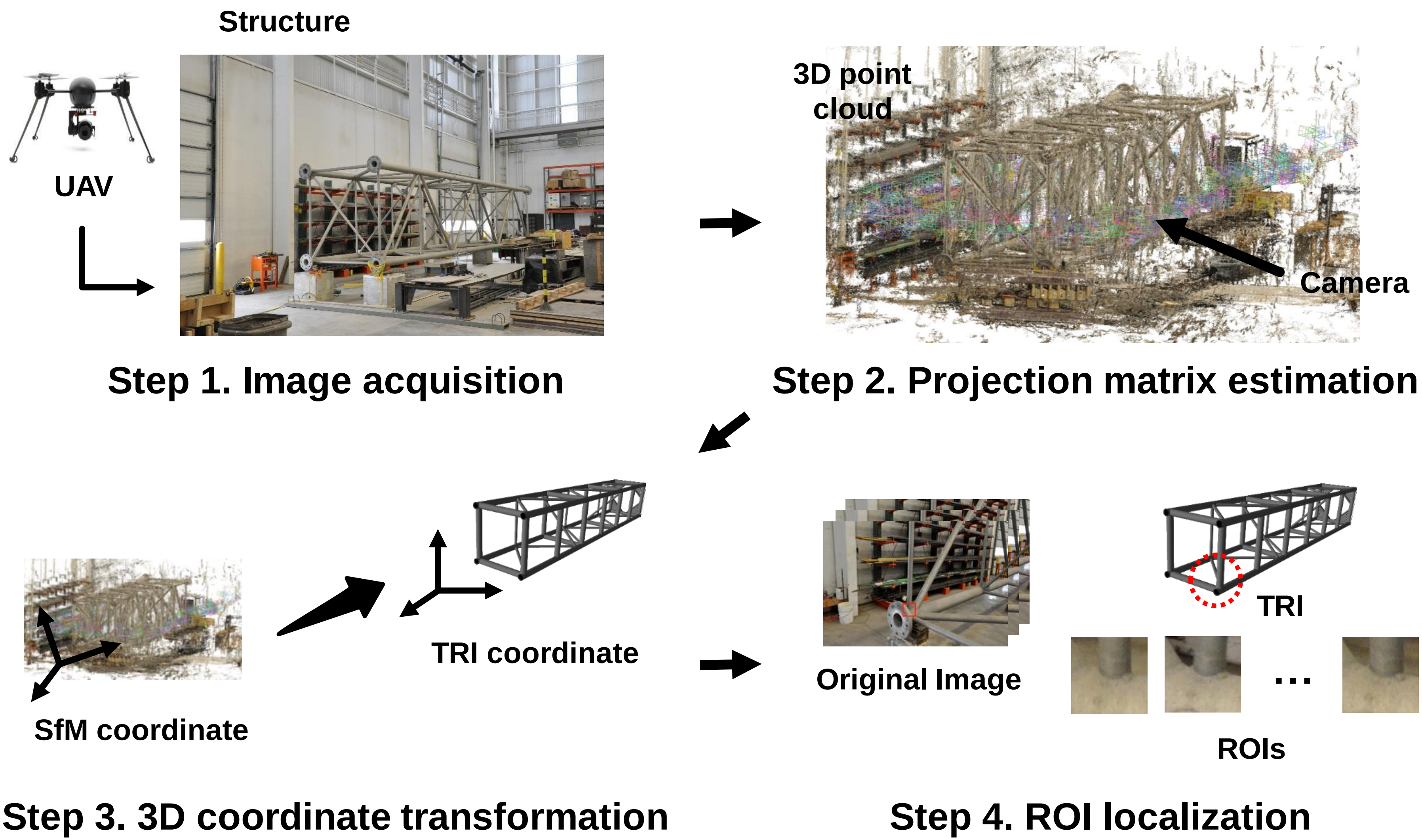
ROI

i : Image number

$$\mathbf{x}_i = \boxed{\mathbf{P}_i}\mathbf{X}$$

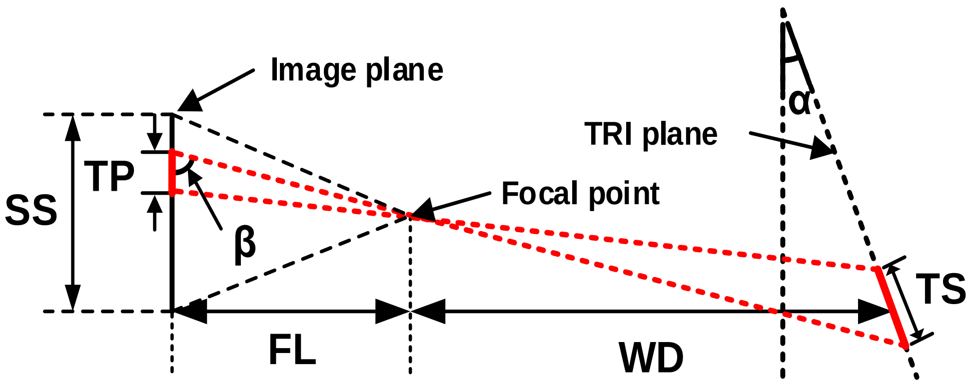
2D point on image i **3D point**

Overview of the Technical Steps



Step 1: Image Acquisition Guideline for Clear Visibility

1. Working distance



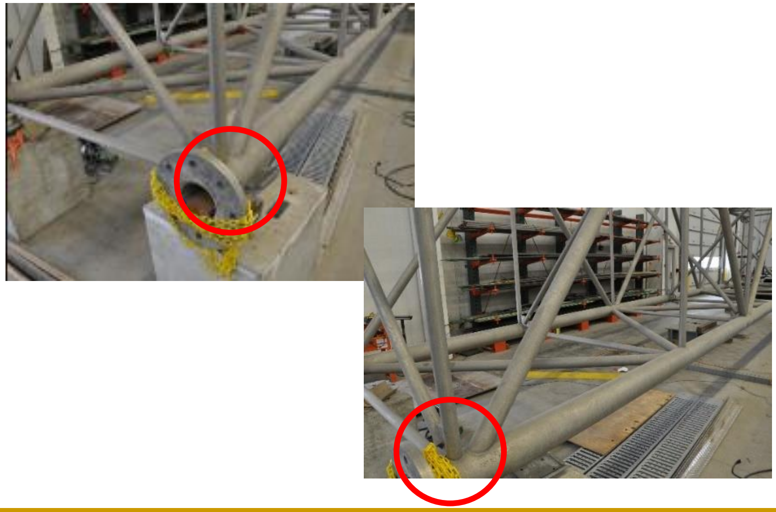
Example
- SR = 4,288 px (Sensor resolution-Width)
- SS = 23.6 mm (Sensor size)
- TS = 63.5 x 2 mm (TRI size – diameter)
- TP = 127 px (the min. size of the ROIs)
- FL = 18 mm (focal length)
- α = 0 ~ pi/3
- β = 0.92 ~ pi/2

WD = 2,200 mm

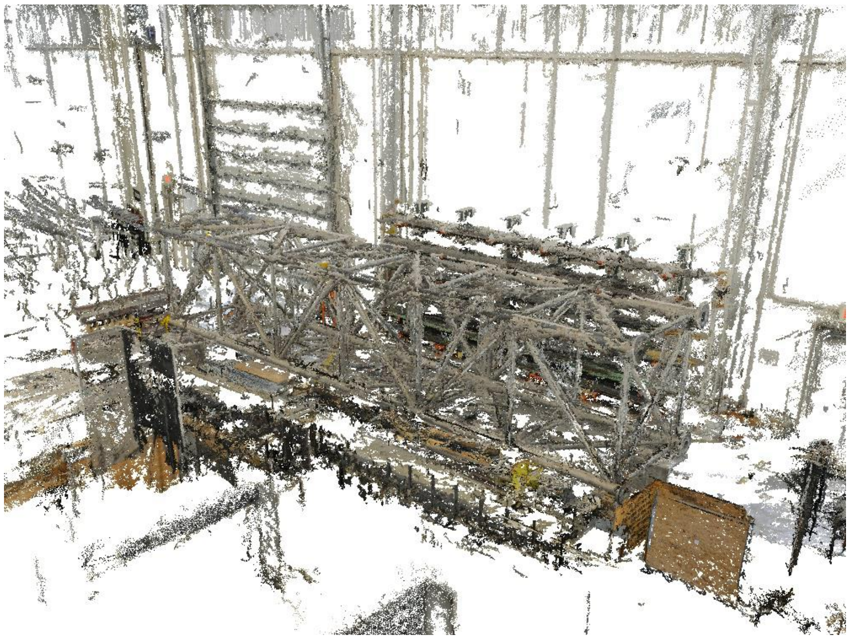
2. Motion blur

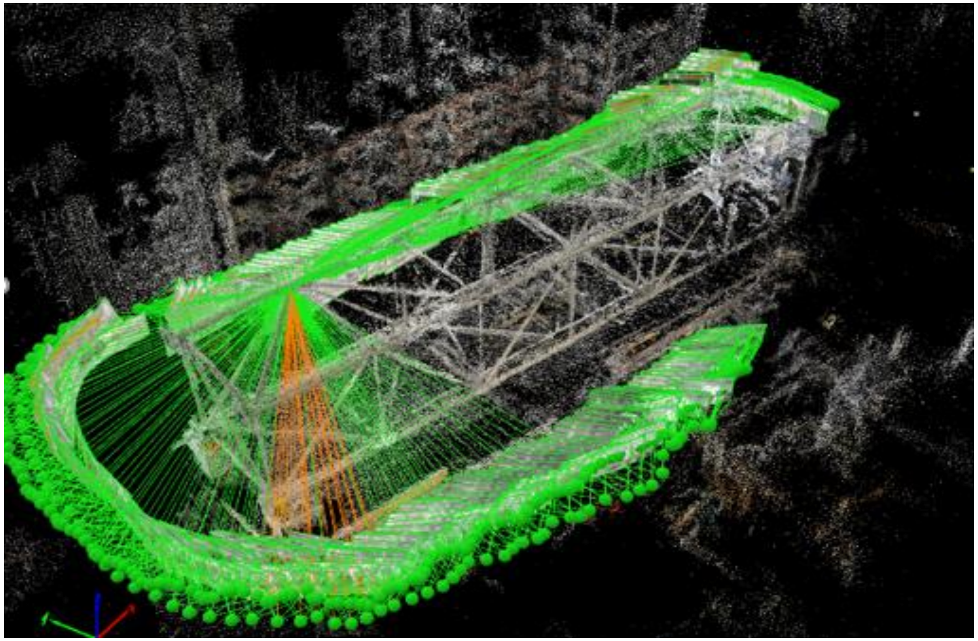
- Flying speed
- Light condition
- Shutter speed
- Vibration on the platform

3. Occlusion



Step 2: Projection Matrix Estimation using Structure-from-Motion



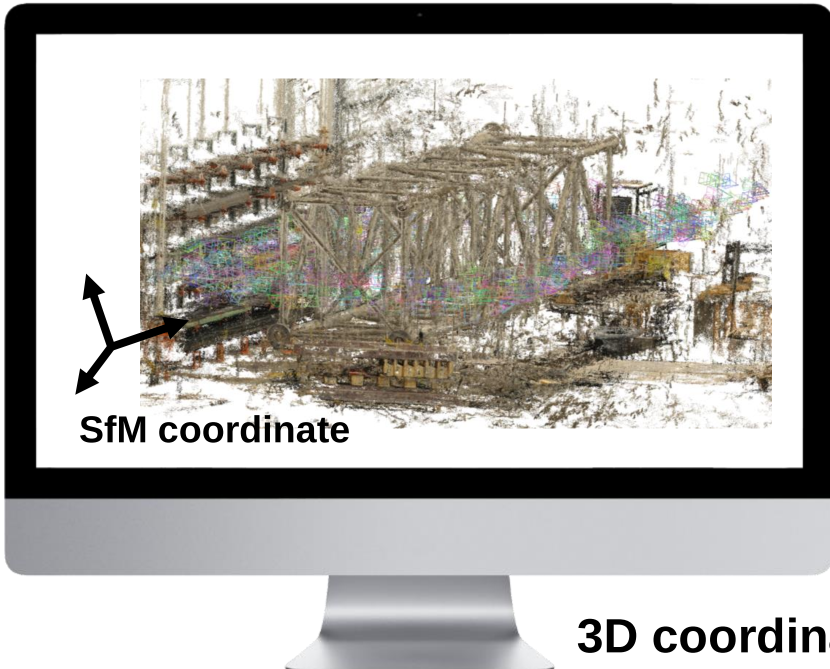


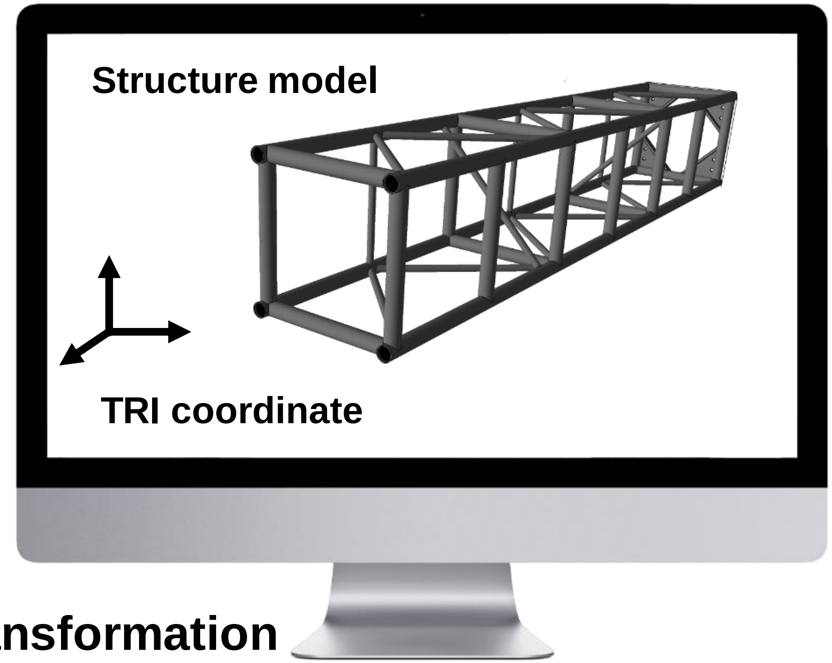
SfM coordinate

$$x_i = P_i^S X^S \quad (i = 1, 2, \ldots, n)$$

\# of images

Step 3: 3D Coordinate Transformation





3D coordinate transformation (for synchronization)

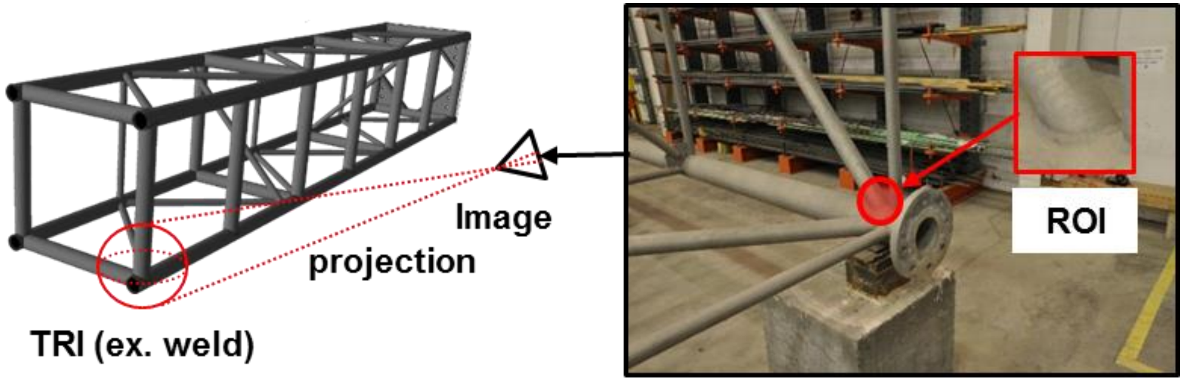
$$x_i = P_i^T X^T \quad \left(i = 1,\ 2,\ \ldots,\ n\right)$$

7-parameter transformation (Horn’s method) : translation, rotation, and scaling.

TRI coordinate

$$X^T = \boxed{M} X^S \quad \Rightarrow \quad P_i^T = P_i^S \boxed{M}^{-1}$$

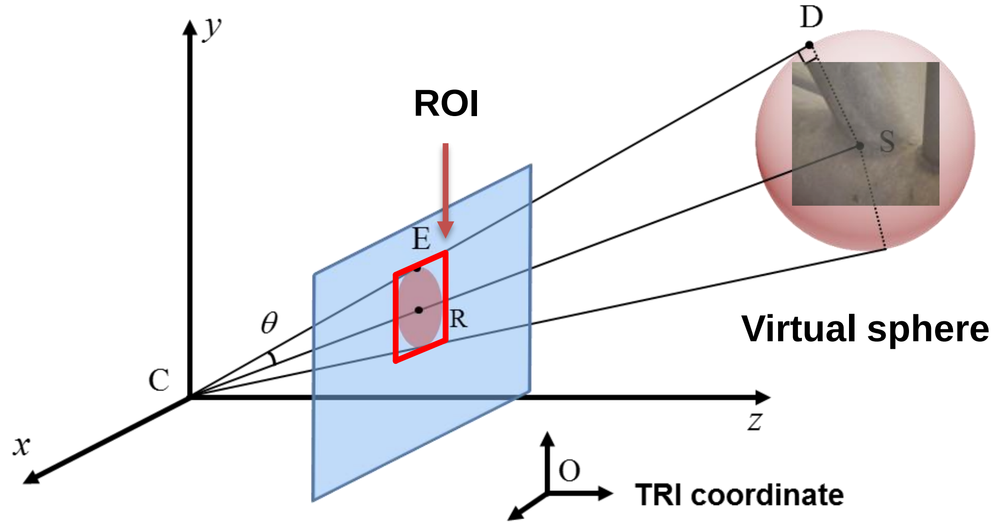
Step 4: ROI Localization



Projection of a virtual sphere to an image: Compute a projected area on an image corresponding the TRI (theoretical derivation of sphere projection in Chapter 3.2.4)

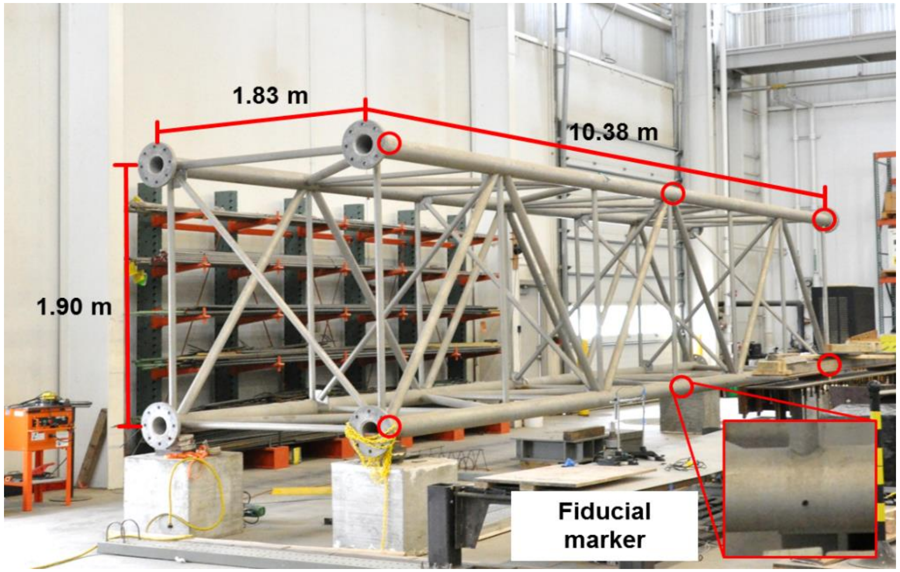
Constraints 1: Bounding boxes should be entirely visible on the image

Constraints 2: Bounding boxes should be large enough to obtain useful ROIs

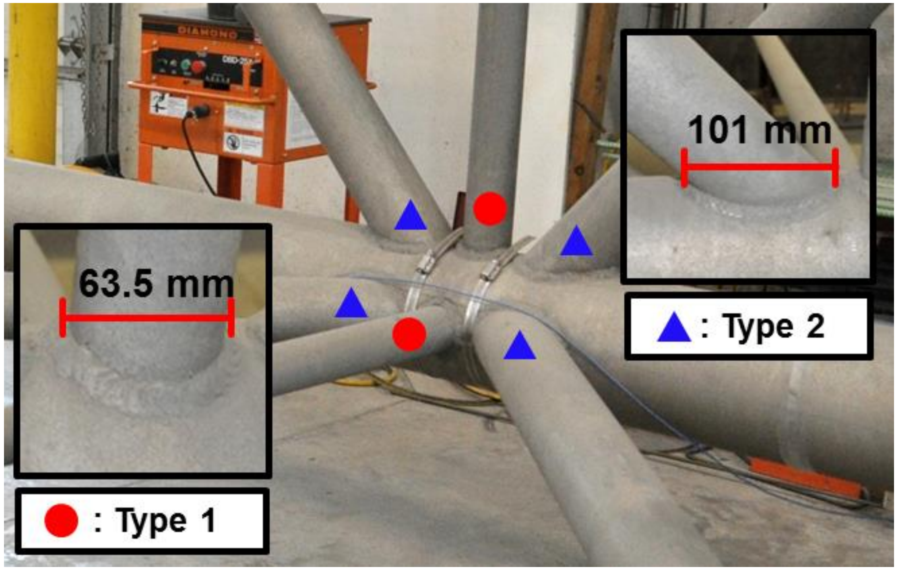


Experimental Validation: Description of the Test Truss Structure

Full-Scale Truss in Bowen



Weld Connection



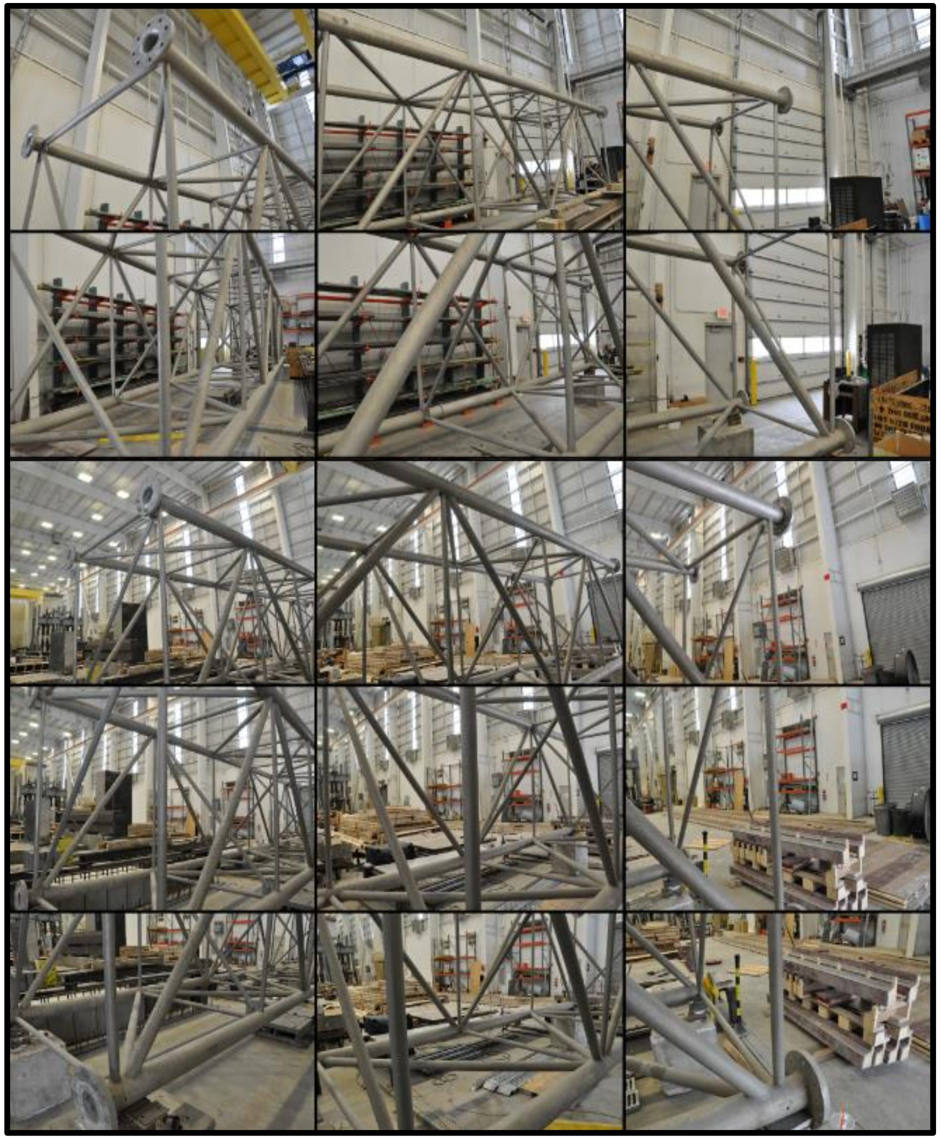
TRI information (weld connection)

- 118 Weld connections (TRIs)
- Known 3D coordinates for each weld
- Multiply a factor (2) to a diameter in each weld type

3D Coordinate Transformation

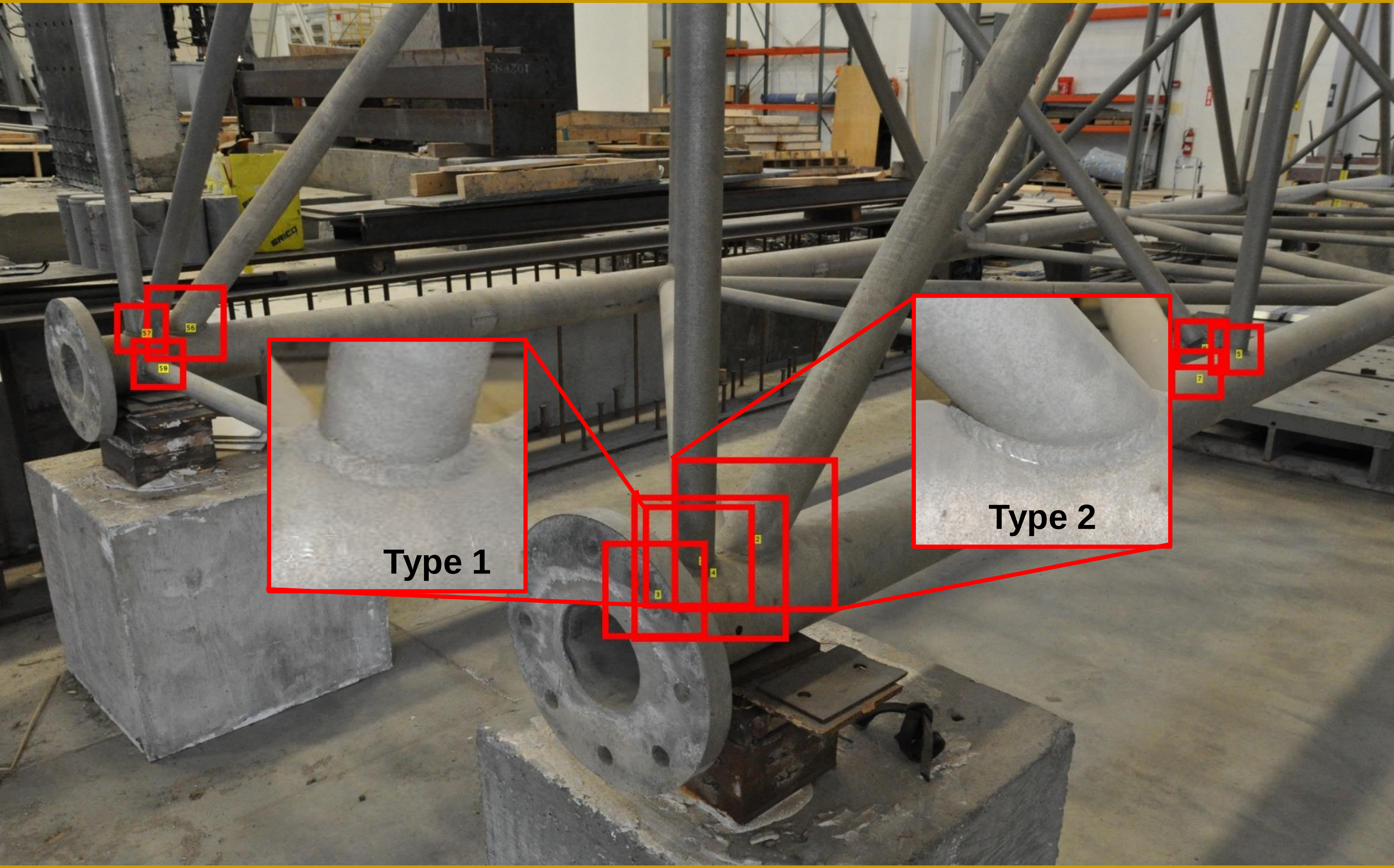
- Twelve reference points
- 3D point registrations using manually matching the points (but, possibly, automated)

Sample Images and SfM Model Construction

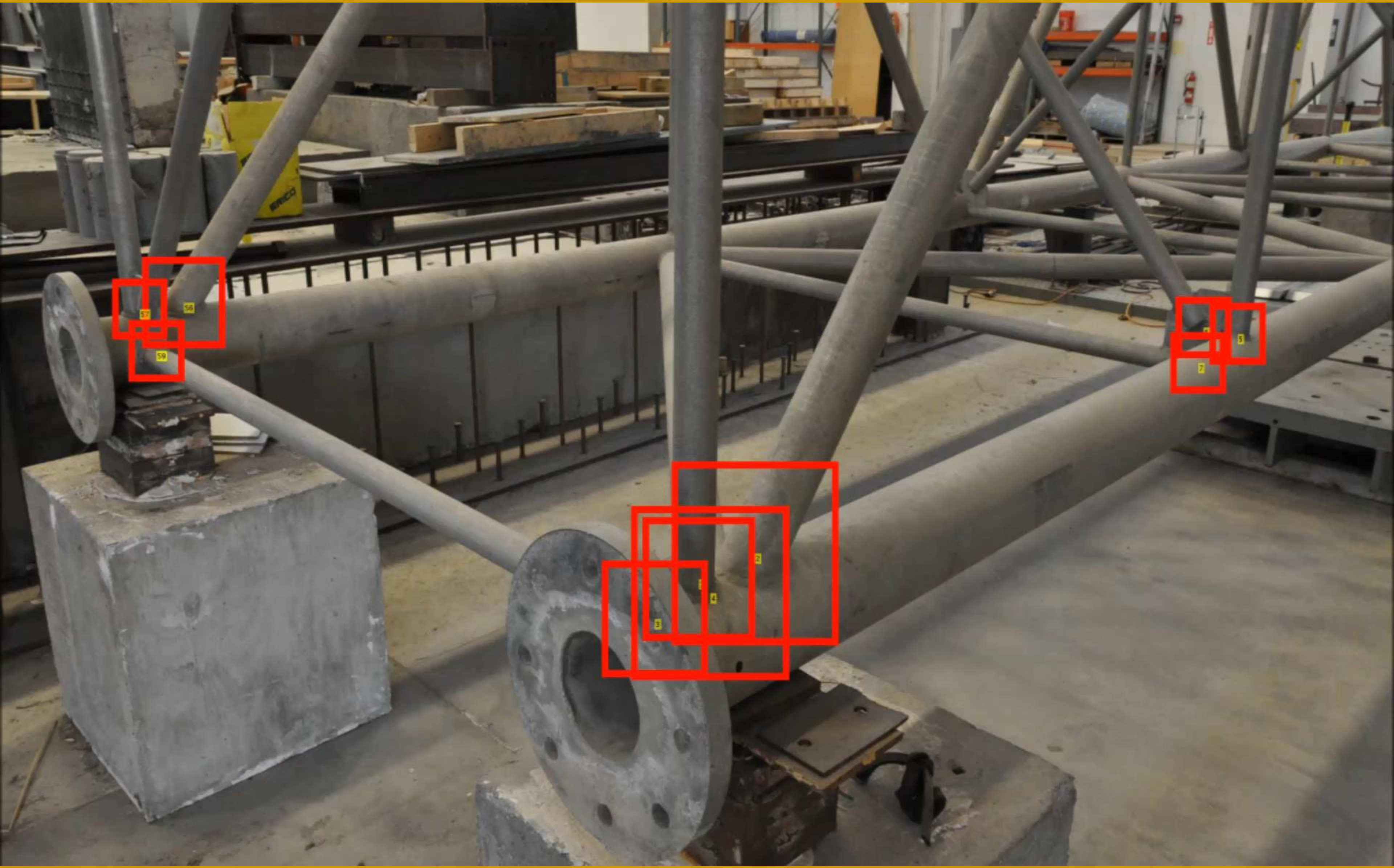


Date	Mar 1st
Time	12:10am – 1:20am
Light	Interior Light
# of images	836
Camera model	NIKON D90 (DSLR)
Focal length	F/10, 1/30s
Image size	4266 X 2848

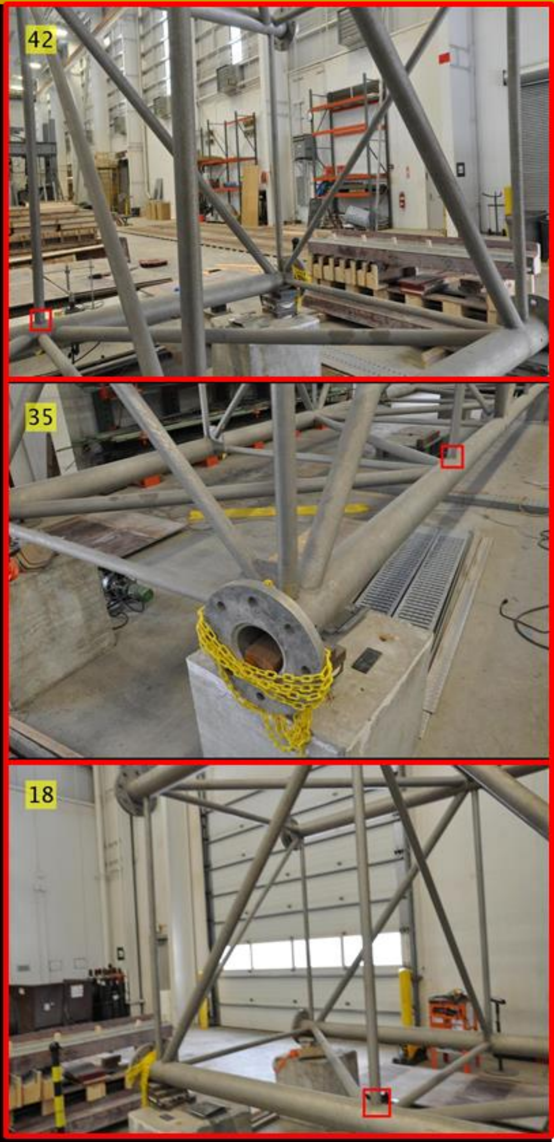
Localized ROIs on the Image



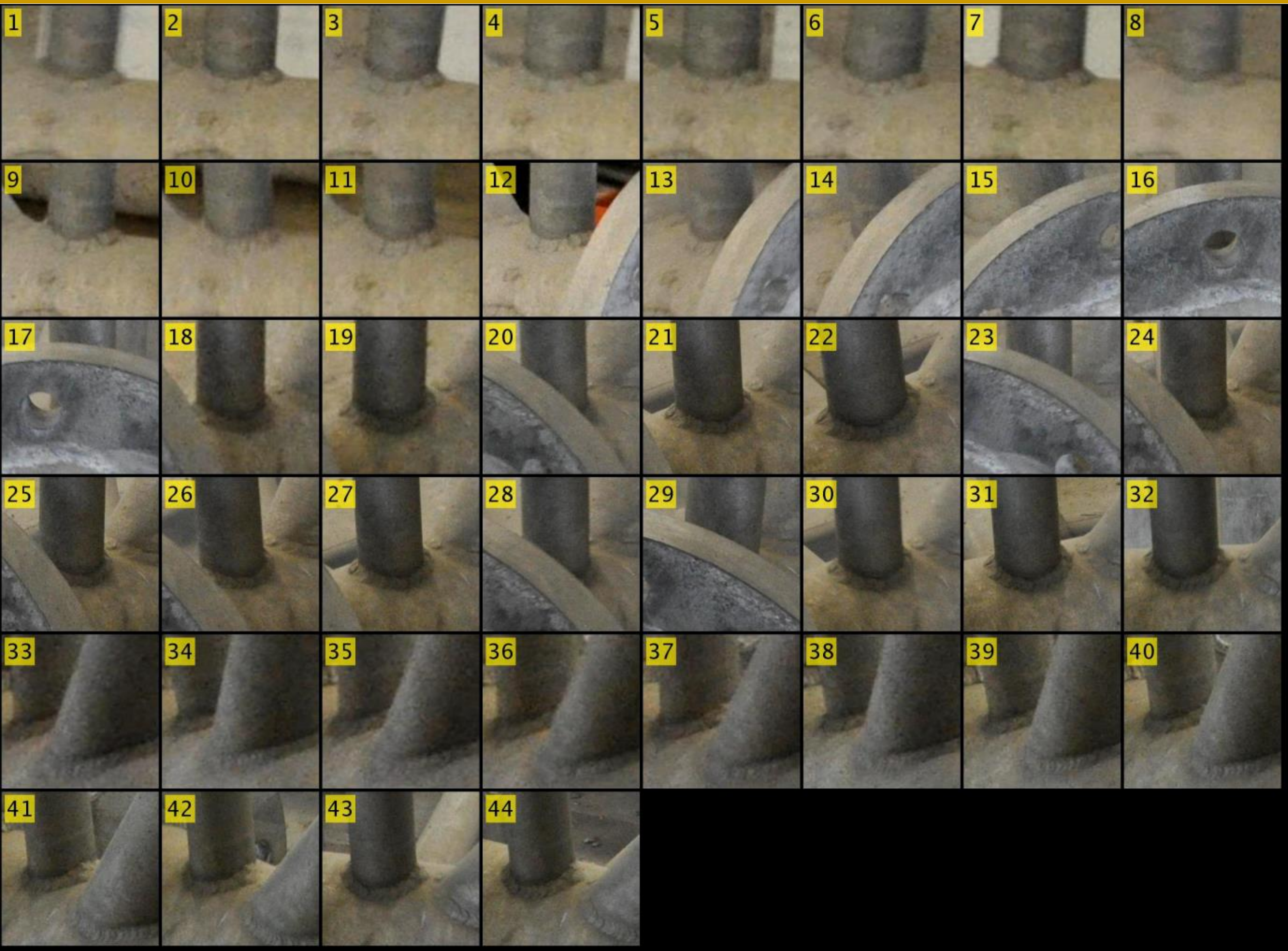
All Bounding Boxes (ROIs) on Each Images

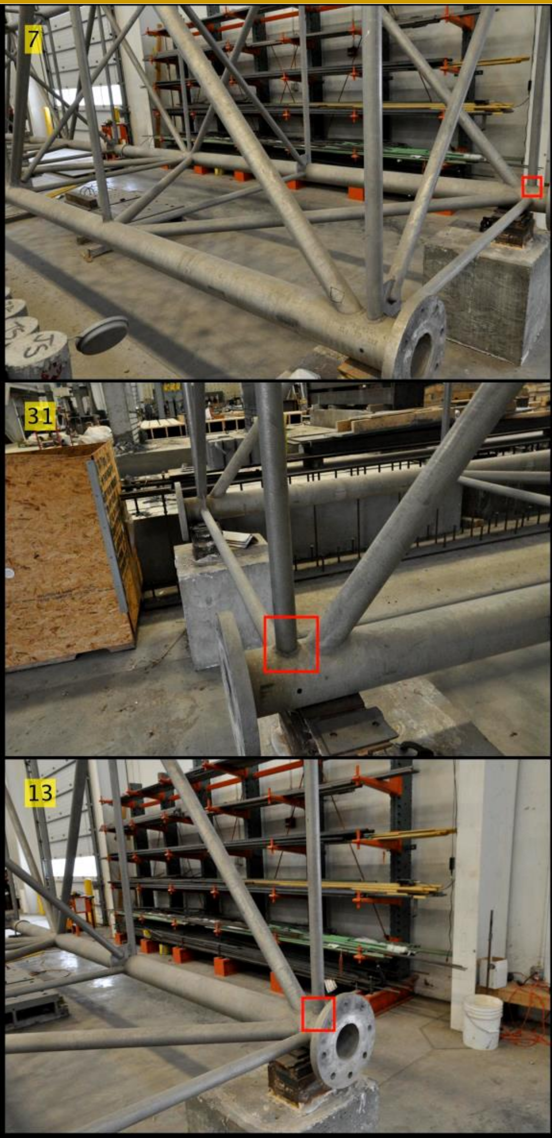


A Sample of Weld Connection (TRI) Localization (Weld 34)



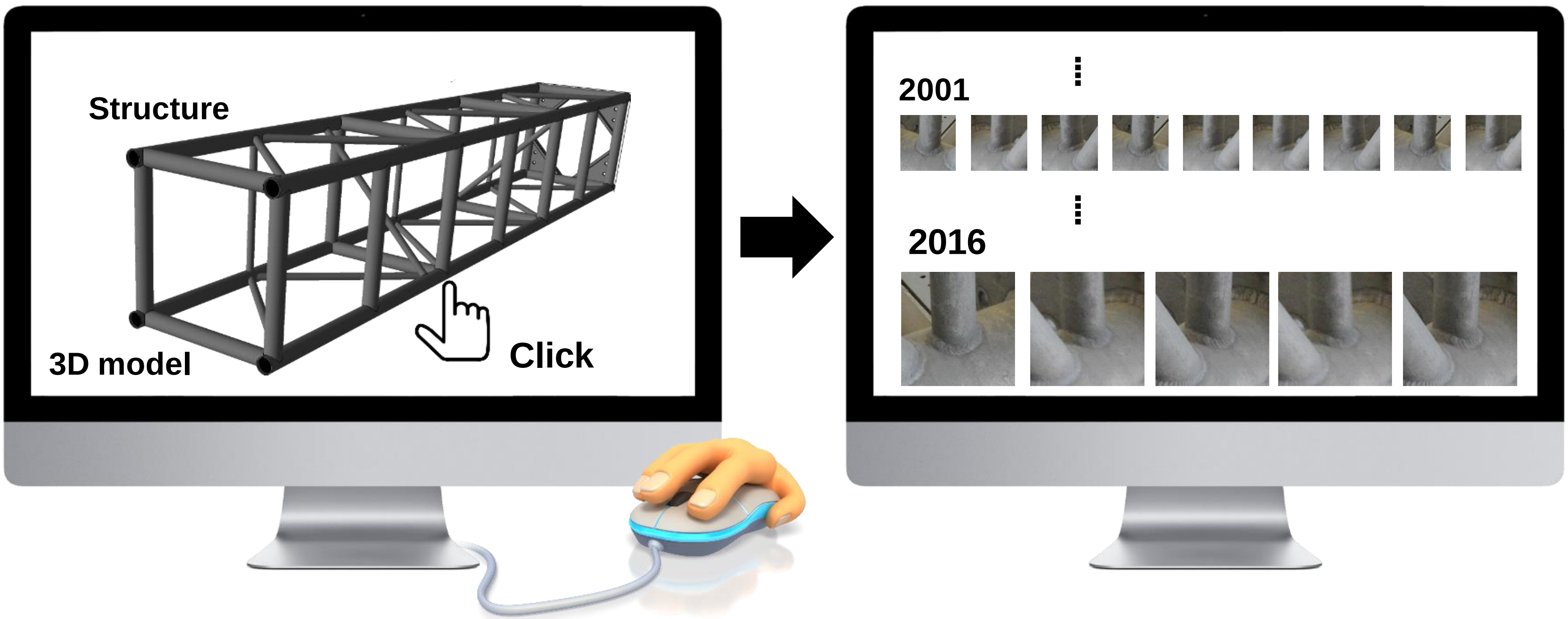
Localization of All TRIs (Weld Connection)





ID: Weld_1 Detected images: 44

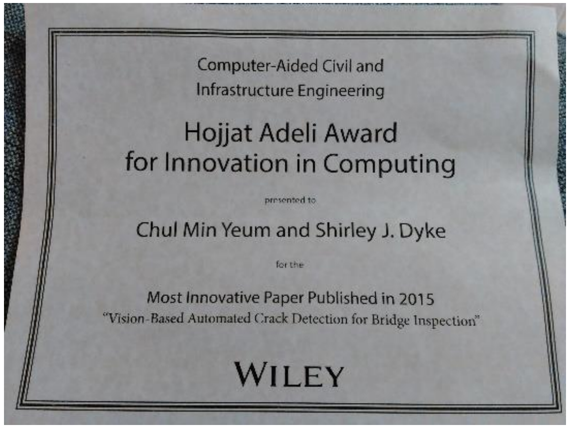
Potential Software: Human-based Visual Inspection Scenario using the Developed Approach



Related Publication and Project

Journals

- **Chul Min Yeum** and Shirley J Dyke. "Vision-Based Automated Crack Detection for Bridge Inspection." Computer-Aided Civil and Infrastructure Engineering 30, no. 10 (2015): 759–770. **(selected as Hojjat Adeli Award 2015)**
- **Chul Min Yeum,** Jongseong Choi, and Shirley J. Dyke. "Autonomous image localization for visual inspection of civil infrastructure." submitted to Smart Materials and Structures (received "minor revision") (2016).
- **Chul Min Yeum**, Jongseong Choi, and Shirley J. Dyke. "Region of Interest Localization and Classification for Vision-based Damage Detection of Civil Infrastructure." in preparation (2016).


Computer-Aided Civil and Infrastructure Engineering

Hojjat Adeli Award for Innovation in Computing

presented to

Chul Min Yeum and Shirley J. Dyke

for the

Most Innovative Paper Published in 2015

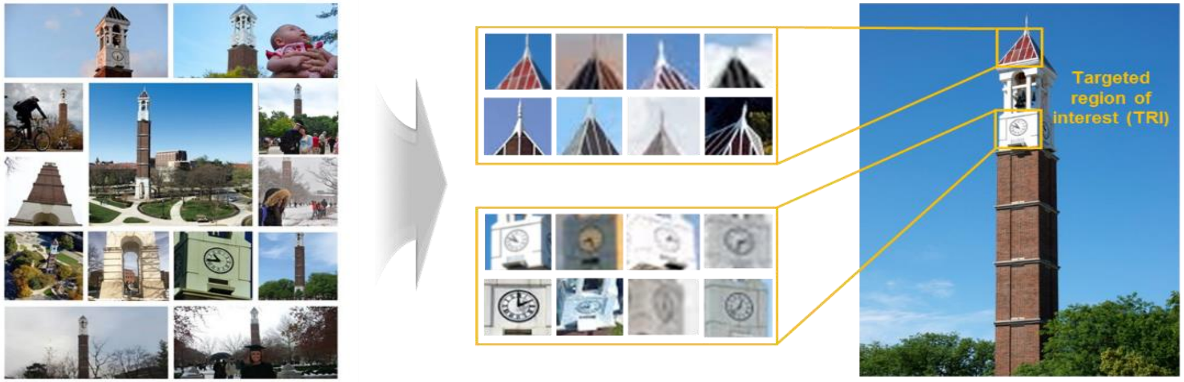
"Vision-Based Automated Crack Detection for Bridge Inspection"

WILEY

Conference proceedings

- Shirley J. Dyke, **Chul Min Yeum**, Christian Silva, and Jeff Demo. "Applications of computer vision in structural health monitoring." (a keynote speech) Proceedings of the 7th Structural Health Monitoring and Intelligent Infrastructure, Italy, July1-4, 2015.
- **Chul Min Yeum** and Shirley J. Dyke. "Vision-based Automated Visual Inspection of Large-scale Bridges". Sixth World Conference on Structural Control and Monitoring, July, 2014.

EAGER: Active Citizen Engagement to Enable Lifecycle Management of Infrastructure Systems (NSF #1645047, 09.01.16 – 08.31.16)



Citizen Science Images (CIM) **Region of interest (ROI)** **Structure for visual evaluation**

Research Topic 1: Conclusions and Future Work

Conclusions

- A novel automated image localization technique is developed to extract regions of interest on each of the images in a large set of images before utilizing vision-based inspection techniques.
- Analysis of such highly relevant and localized images will enable efficient and reliable visual inspection.
- The capability of the technique is **successfully demonstrated** to extract the ROIs of weld connections using **a full-scale highway sign structure**.

Future Work

- Promising technology applicable to drone-based visual inspection will be explored to build more robust, efficient, and fast systems. Recent developments in depth cameras, including Lidar, time-of-flight (ToF) cameras, and RGB-D cameras will enhance an inspection by adding an extra depth dimension, which is not exactly captured with human eyes. These new devices represent an opportunity for 3D modeling of a structure and localization (navigation) with pre-built maps.
- The autonomous image localization technique will be explored to facilitate lifecycle management of infrastructure systems using citizen science and crowdsourcing images, as a part of NSF-1645047.

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3. **Research Topic 2: Visual Data Classification in Post-event Building Reconnaissance (Chapter 5)**
4. Conclusions

Motivation of the Research

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

Objective and Contributions of the Research

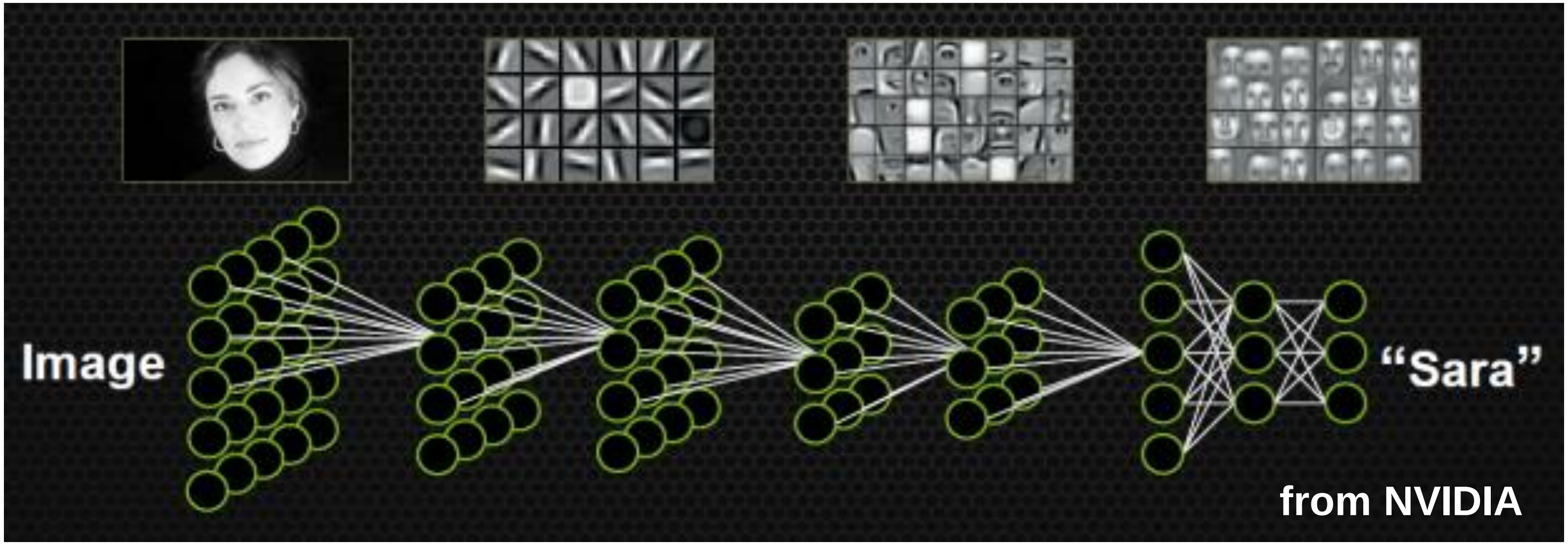
Objective

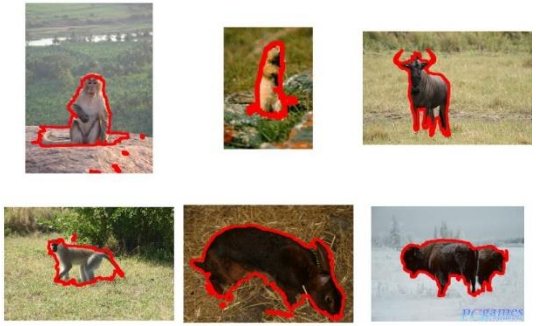
Develop **an image annotation method** through autonomous detection, classification, and evaluation of visual data that will support scientific research using **deep convolutional neural network** algorithms.

Contributions

- Successfully implement deep convolutional neural network for post-reconnaissance images;
- Build a large-scale database for real-world disaster images and their ground-truth annotations intended for computer vision research;

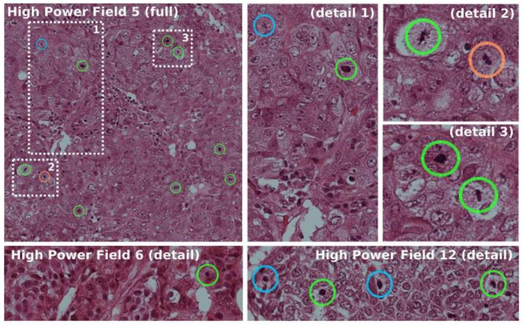
Deep Convolutional Neural Network (CNN)





Object segmentation

Drone navigation



Mitosis detection

Examples of Image (Scene) Classification and Object Detection

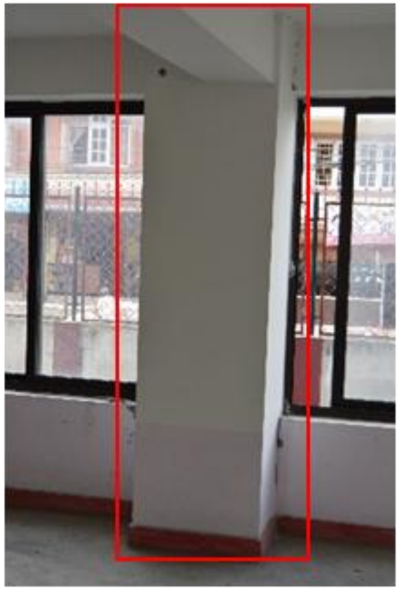
Image Classification

Collapse

Building façade

A Class of an image

Object Detection



Column

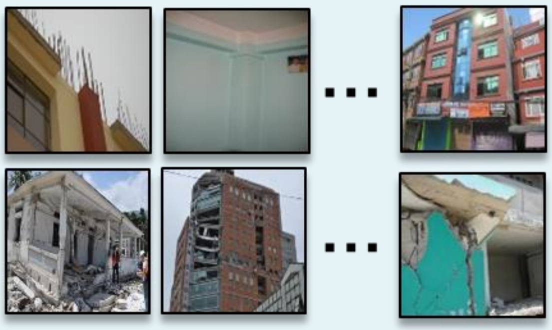
Spalling

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

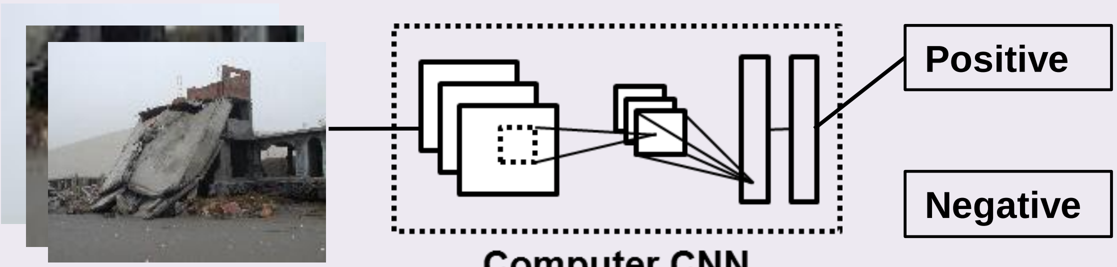
Collapse

Spalling/Flaking

School building

Façade

A process of training a binary classifier



Ground-truth image

Computer CNN features

Corresponding label

Positive and Negative Images for Training

Image classification
(for collapse classification)

A set of images collected at the field

Collapse images
(positive)

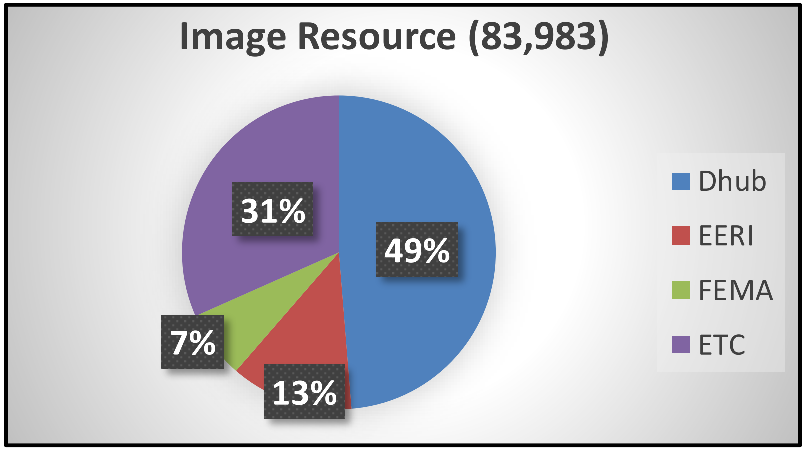
The rest
(negative)

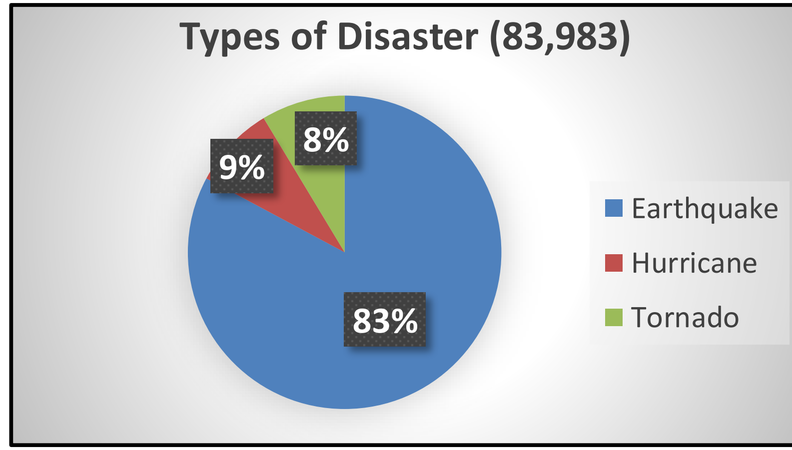
Object detection
(for spalling detection)

Positive

Negative

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

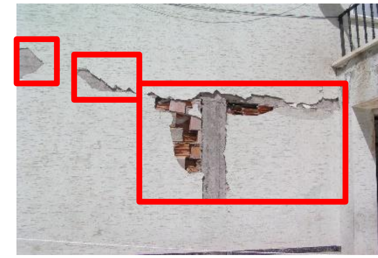



Image including

- 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

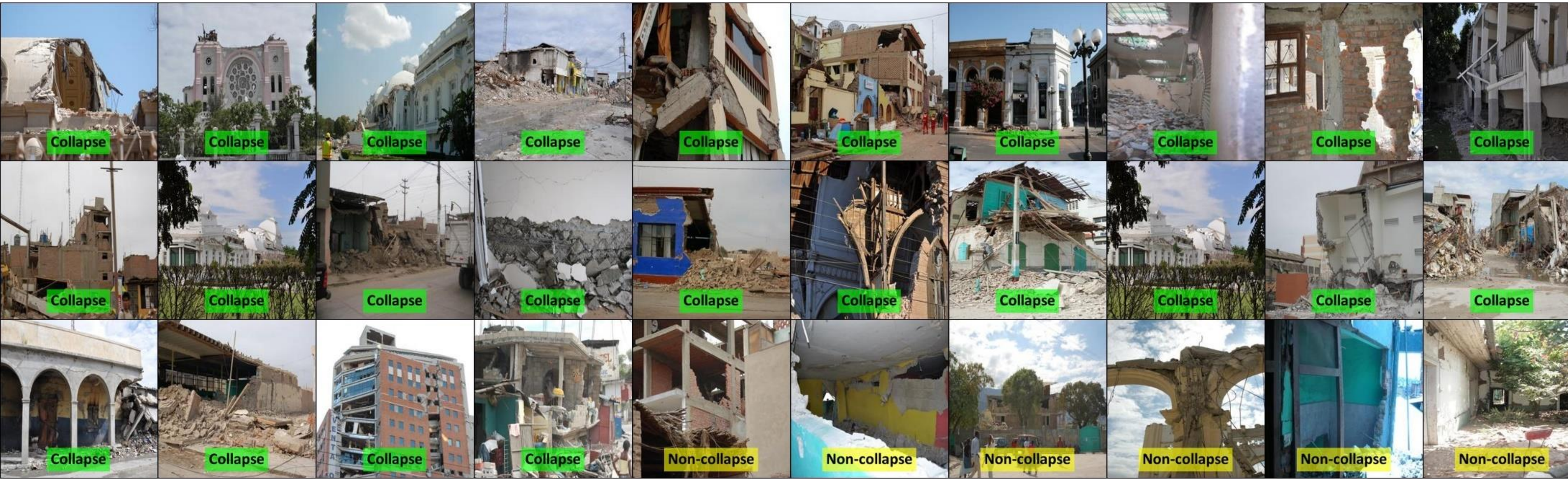
Irrelevant images

Undamaged building

Positive

Negative

Samples of Images with the Predicted Classes

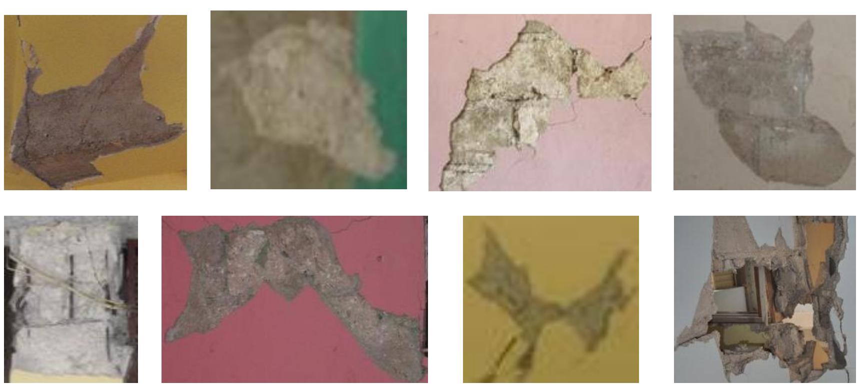


417 (TP)	45 (FN)
67 (FP)	788 (TN)

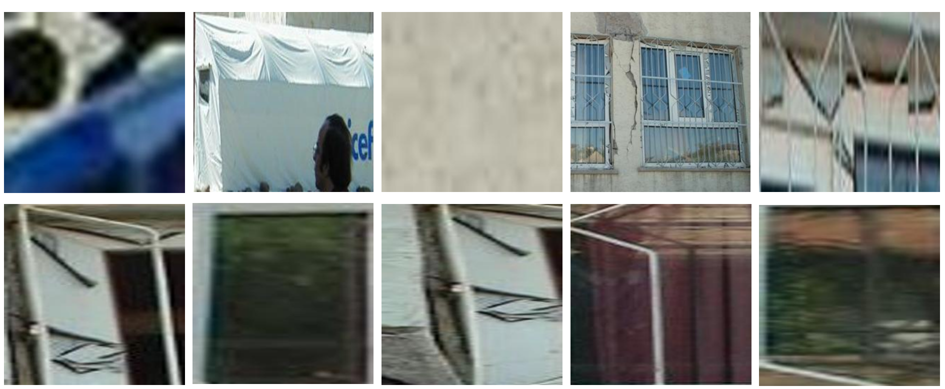
True-positive: 90.26%
True-negative: 92.16%
Precision : 0.862 **(TP/(TP+FP))**

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

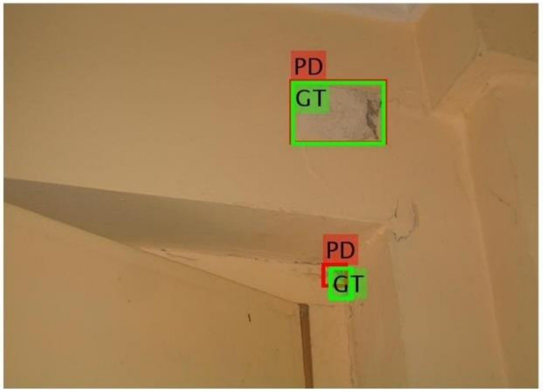


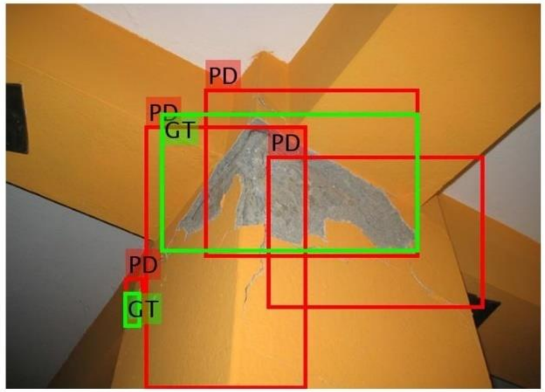
Positive

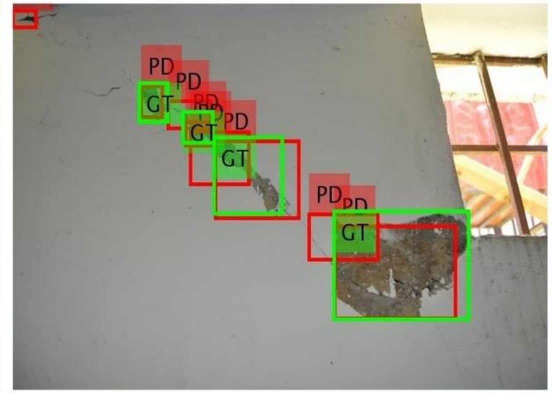


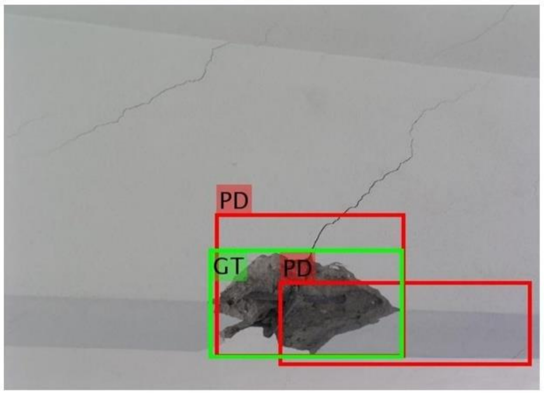
Negative

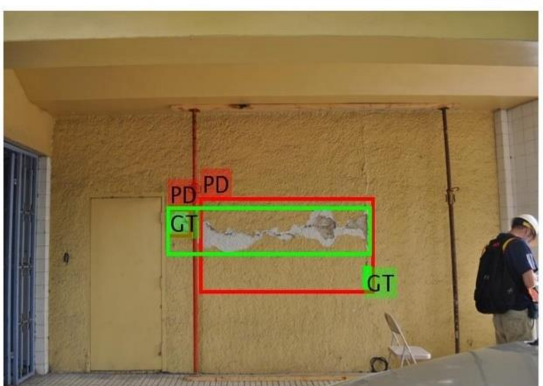
Samples of Spalling Detection











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

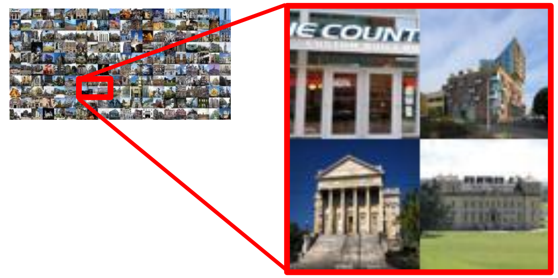
40.48% of true-positive (619/1529)

62.16% of detection rate (506/814)

Lessons Learned from This Study

1. Unbiased Sample Data

VS



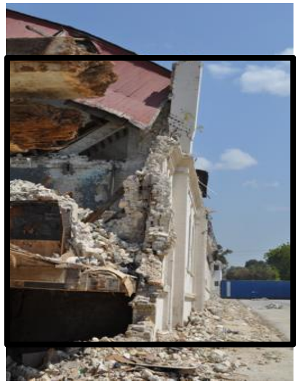
?

Collapsed building

Existing labeled dataset (building) – Places2 dataset

Undamaged building

2. Input Images of CNN (Input of CNN should be square.)



VS

Our image

Imagenet

Current

Related Publications and Projects

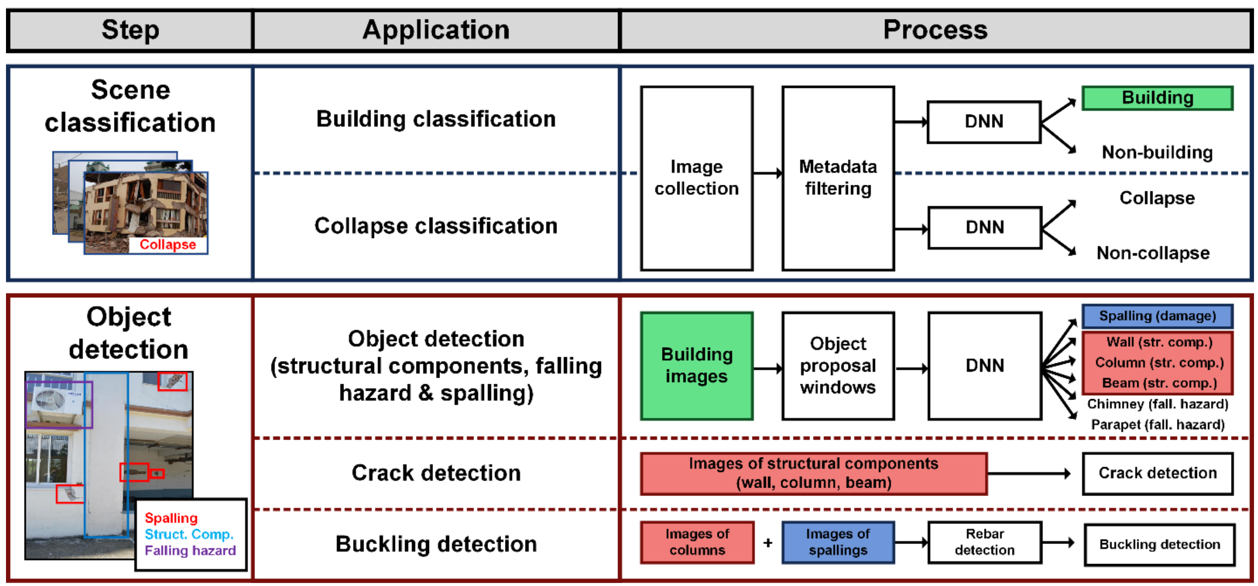
Journals

- **Chul Min Yeum**, Shirley J. Dyke, and Julio A. Ramirez. “Visual Data Classification in Post-Event Building Reconnaissance.” submitted to Engineering Structures (2016).

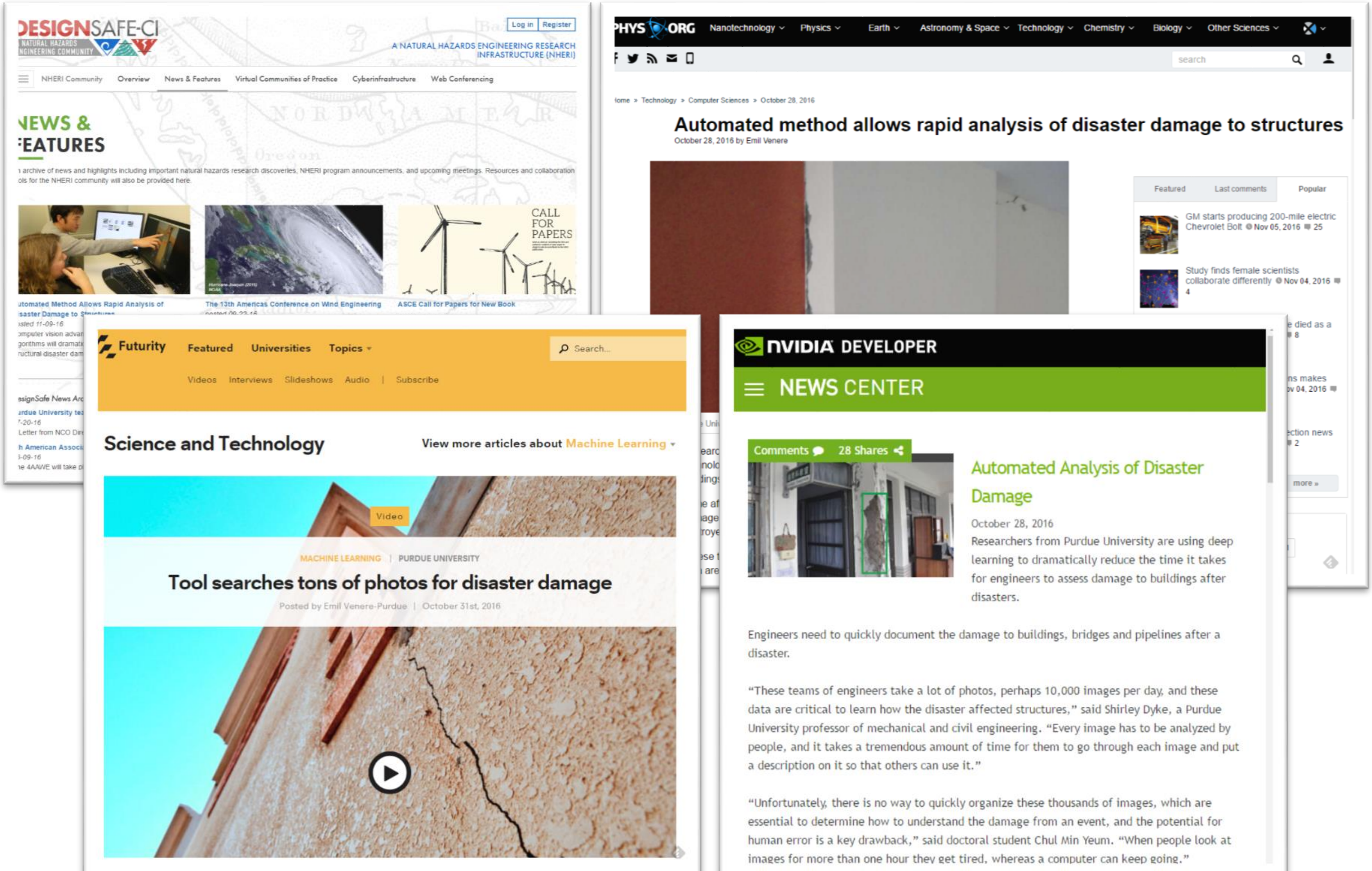
Conference proceedings

- **Chul Min Yeum**, Shirley J. Dyke, Julio A. Ramirez, Thomas Hacker, Santiago Pujol and Chungwook Sim. “Annotation of Image Data from Disaster Reconnaissance,” Proceedings of the 16th World Conference on Earthquake Engineering, Santiago, Chile, Jan. 2017.
- **Chul Min Yeum**, Shirley J. Dyke, Julio A. Ramirez, and Bedrich Benes. “Big Visual Data Analysis for Damage Evaluation in Civil Engineering,” Proceedings of International Conference on Smart Infrastructure and Construction, Cambridge, U.K. June 2016.

CDS&E: Enabling Time-critical Decision-support for Disaster Response and Structural Engineering through Automated Visual Data Analytics (NSF #1608762, 07.15.16 – 06.30.19)



Our Project Appeared in the Press



Research Topic 2: Conclusions and Future Work

Conclusions

- A method to perform out automated post-disaster image classification is developed which functions by processing and analyzing visual data.
- The method is demonstrated for specific classification examples focused on collapse classification and spalling detection.
- However, the general method can be applied to other scenes or objects, or other civil applications that require detecting visual contents.

Future Work

- More cases for application of the developed image classification and object detection method will be implemented (e.g. the objects and scenes listed in chapter 5.30) and time-critical needs will be explored.
- This work is ongoing project, as a part of National Science Foundation under Grant No. NSF-1608762, and related works will continue to build more robust and various classifiers by expanding the number of image collections and their ground-truth annotations

Presentation Outline

1. Introduction
2. Research Topic 1: Autonomous Image Localization (Chapter 3)
3. Research Topic 2: Visual Data Classification in Post-event Building Reconnaissance (Chapter 5)
4. **Conclusions**

Acknowledgment

Committee Members


Shirley Dyke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Santiago Pujol


Zygmunt Pizlo

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

Other Researchers

- Faculties: Robert Connor (Purdue), James bethel (Purdue), Chungwook Sim (U of Nebraska), Matt Hebdon (Virginia Tech)

- Colleagues: Jongseong (Purdue), Christian (Purdue), Lucas (Purdue).

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PURDUE UNIVERSITY

NSF

LUNA DEFYING IMPOSSIBLE.

Questions and Answers