Automated Detection of Pre-Disaster Building Images

from Google Street View

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Post-disaster Reconnaissance

Hurricane, Tornado, Flood





Major hurriane events in USA

- Harvey, Irma, Maria in 2017
- Patricia in 2015
- Sandy, Issac in 2012
- Rita, Katrina in 2005



Post-disaster reconnaissance

- Conducting rapid structural evaluation
- Collecting data (e.g. images, measurement)
- Evaluating flood damage
- Reporting repair costs

Collection of Post-disaster Reconnaissance Images





Robotic platform

Google flickr

Social media

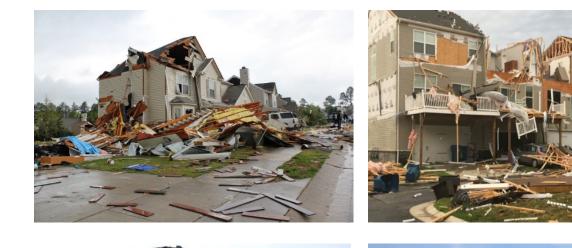


Wearable dev.





Crowd sourcing







Collecting images from damaged buildings

Various image collection platforms

Motivation: How to Make Those Images More Useful?



Is this sufficiently informative?



After Harvey hurricane in Rockport, TX (Courtesy of Tom Smith)

Motivation: Integration of Pre-disaster Images using Google Street View



Before Harvey hurricane in Rockport, TX (Google Street View)

Images from various viewpoints

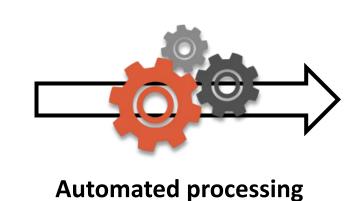
Objectives

Automatically extracting and detect pre-disaster building images from Google Street View images using computer vision techniques

Advantages

- Fully-automated and rapid extraction of pre-disaster building images
- Exploiting high-resolution building images under various viewpoints/from various years

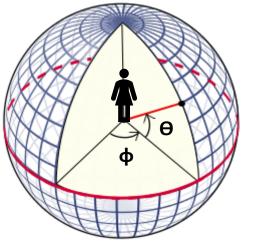




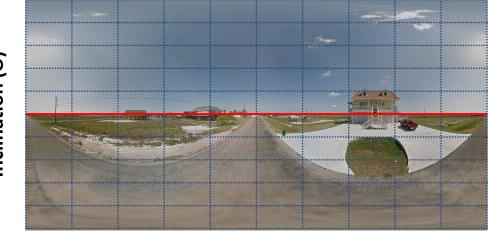


360° Panorama and Rectilinear Image

360 panorama (stored in Google Street View)



Inclination (⊖)



Azimuth (φ)

Rectilinear image (what we have seen from its viewer)







Rectilinear with an incorrect direction



Rectilinear with a proper direction

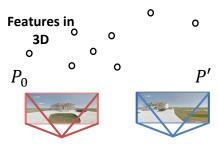
- Time consuming process to observe pre-disaster building images
 Implementation of automated building detection
- Unwanted large distortion of a building on rectilinear images

 Optimal viewing angle estimation using multi-view geometry

Overview of the Technical Steps



(a) Read input GPS from a geo-tagged image



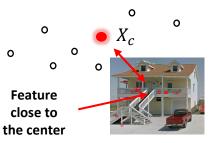
(f) Estimate projection matrices



(k) Detect a building from the optimal RTs



(b) Download 360° panoramas (PN) near input GPS



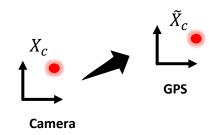
(g) Define a approximate location of the building



(I) Localize building images



(c) Generate two rectilinear images (RT) from the nearest PNs to the input GPS



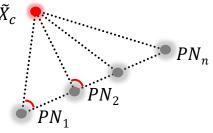
(h) Transform the coordinate system



(d) Detect a building from each of these RTs



(e) Extract and match features

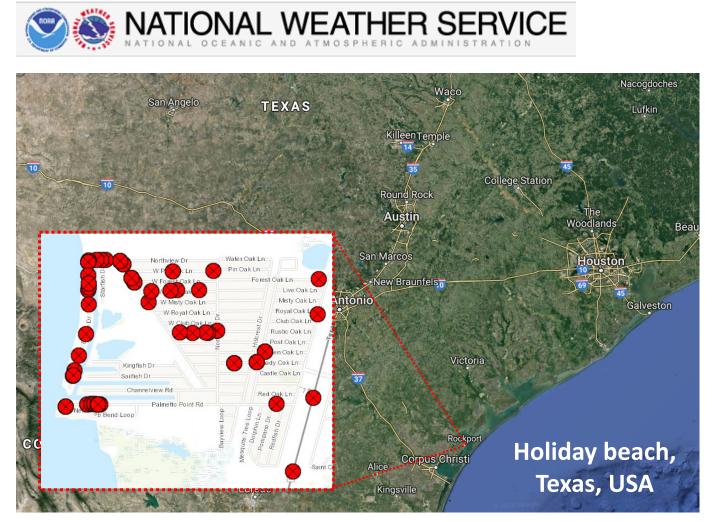


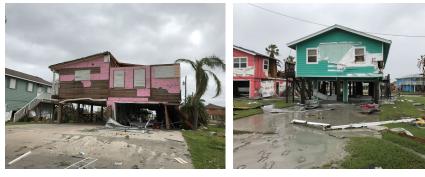
(i) Compute a direction for each PN

(j) Extract the optimal RTs by considering their direction

- Stage 1: Download the panoramas (PN) near a target building
- Stage 2: Compute the building location in GPS
- Stage 3: Generate the optimal rectilinear images (RT) using their proper direction
- Stage 4: Detect the target building from each of rectilinear images

Experimental Study: Input Geo-tagged Reconnaissance Images









Post-disaster reconnaissance images



Training a House Image Detector using RCNN

- Architecture: Faster R-CNN and ResNet
- # of houses: 100 (at holiday beach)
- # of bounding boxes: 3500
- # of images: 1100
- Learning rate: 0.001
- Momentum: 0.9
- Weight decay: 0.0005
- Confidence threshold: 0.5
- NMS threshold: 0.3
- Training/testing: 60/40 %

Configuration for training

Testing result: 85.4% (average precision)

Labeled house Not labeled







Labeling house images for training a classifier

Samples of house detection testing results

Sample Result: Providing an Input Geo-tagged Image



Input: Geo-tagged post-disaster images collected during residential building reconnaissance missions

Sample Result: Downloading the Panoramas Near a Target Building (Stage 1)



Input: Geo-tagged post-disaster images collected during residential building reconnaissance missions



Raw 360° panorama images downloaded from Google Street View

Sample Result: Computation of the Building Location (Stage 2)

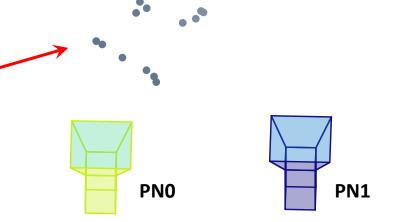


Input: Geo-tagged post-disaster images collected during residential building reconnaissance missions



Feature extraction and match

One of the points is selected as the house location (close to the center of the house)

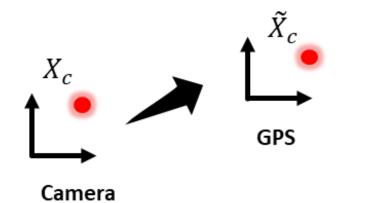


3D point cloud created from camera geometry

Sample Result: Generation of Optimal Rectilinear Images (Stage 3)



Input: Geo-tagged post-disaster images collected during residential building reconnaissance missions

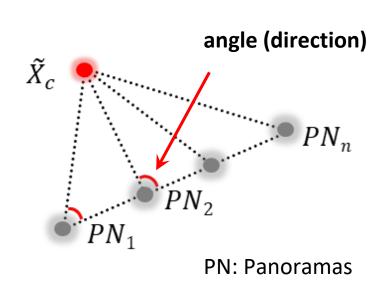


Known

- Cam. locations in the camera coordinate
- House location in the camera coordinate (X_c)
- GPS locations of the panoramas (cameras)

Unknown

• GPS location of the house (\tilde{X}_c)



Computation of the angle

Sample Result: Generation of Optimal Rectilinear Images (Stage 3)- Continue



Input: Geo-tagged post-disaster images collected during residential building reconnaissance missions







Optimal rectilinear images are generated from each of the panoramas by considering its direction to the house

Sample Result: Detection of the Target Building from RT Images (Stage 4)



Input: Geo-tagged post-disaster images collected during residential building reconnaissance missions









House images can be detected and localized by applying the trained house image detector to the rectilinear images

More Sample Pre-disaster House Images





Post-disaster images

Pre-disaster images extracted from Google Street View

Needs for Extracting Building Images from Various Viewpoints



Post-hurricane image

View of the house obstructed by foreground object(s)











Conclusion and Long-term Vision

- We developed an approach for rapidly and autonomously extracting the pre-event building images from Google Street View.
- We incorporated state-of-art computer vision algorithms to automatically process Google Street View images.
- We successfully demonstrated the capability of our technique using actual post-hurricane reconnaissance images.
- This study provides a great example of how to exploit a large volume of legacy visual database for interdisciplinary research.





Natural disasters Data collection in reconnaissance Automated processing

- Collect more valuable data in the field
- Understand gaps in structural design codes
- Mitigate potential loss in future events



Question ?

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