The University of Washington, eScience Institute

Automatic Detection of Damaged Buildings on Post-Hurricane Remotely Sensed Imagery

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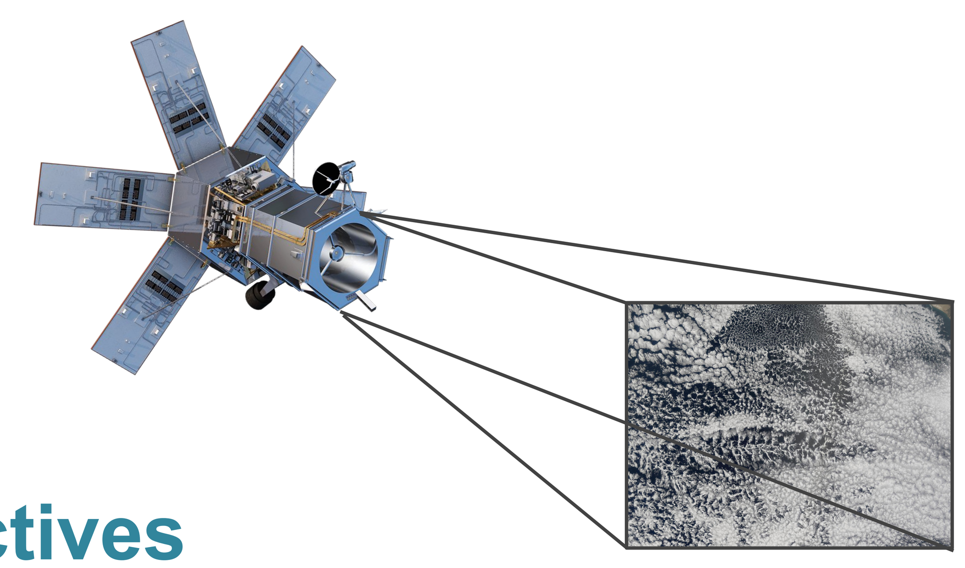
Prioritizing Post-Hurricane Response

Emergency managers of today grapple with post-hurricane damage assessment that largely relies on field surveys and damage reports. We demonstrate how crowdsourced annotations from visually-inspected satellite imagery can provide input to neural object detection models that can automatically identify buildings as having sustained damage after a natural disaster. We create a 2-class data set of damaged and non-damaged buildings and evaluate the performance of different object detection algorithms, including SSD and Faster-RCNN, with the new data set.



Objectives

1) Use crowdsourced annotations from volunteers analyzing post-hurricane satellite imagery to create an input data set for a neural object detection model to distinguish damaged and non-damaged buildings.
2) Train, test, and compare different object detection models to better detect damaged buildings and non-damaged buildings from satellite and aerial imagery.

Data Sources

FEMA
Microsoft
DigitalGlobe
tomnod
Oak Ridge National Laboratory

Process and Model

The data set for input into the object detection models was created by joining:

1. TOMNOD building annotations spanning 19 counties across Texas and Louisiana
2. Building footprint data from Microsoft and Oak Ridge National Laboratories

Building footprints

Rectangular bounding boxes are created around building footprints and are classified as "damaged" or "non-damaged" according to annotations from the TOMNOD volunteers.

Volunteer-labeled data Model output

Data Hosting

A full description of the data creation and modeling process can be found at:
https://dds-lab.github.io/disaster-damage-detection/

Classification Results

The data sets are fed into Tensorflow implementations of two neural object detection algorithms: the Single-Shot Multibox Detector (SSD) algorithm and Faster-RCNN. Model output is evaluated by determining the IoU (intersection-over-union) of model prediction and ground-truth and calculating the average precision within each class. We find the SSD algorithm to be moderately effective at identifying damaged buildings in satellite imagery with our custom data set. These results show the promise of object detection algorithms in helping first-responders to identify areas of comparatively greater damage from satellite imagery alone.

Alternative	Flooded/ Damaged (AP)	Non - damaged (AP)	Mean Average Precision (mAP)
SSD on Satellite Imagery	0.47*	0.62	0.55*
SSD on Aerial Imagery	0.32	0.65*	0.48
Faster R-CNN Satellite Imagery	0.31	0.61	0.46

Future Work

- Train model on additional data
- Test model in new geographic areas and natural disasters
- Try different object detection model architectures

Acknowledgements

We would like to thank the University of Washington, the eScience Institute, and the Data Science for Social Good Program for making this work possible.

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