Disaster Mapping from Satellites: Damage Detection with Crowdsourced Point Labels

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NEURAL INFORMATION PROCESSING SYSTEMS

Abstract

High-resolution satellite imagery available immediately after disaster events is crucial for response planning as it facilitates broad situational awareness of critical infrastructure status such as building damage, flooding, and obstructions to access routes. Damage mapping at this scale would require hundreds of expert person-hours. However, a combination of crowdsourcing and recent advances in deep learning reduces the effort needed to just a few hours in real time. Asking volunteers to place point marks, as opposed to shapes of actual damaged areas, significantly decreases the required analysis time for response during the disaster. However, different volunteers may be inconsistent in their marking. This work presents methods for aggregating potentially inconsistent damage marks to train a neural network damage detector.

Introduction: Point Marks

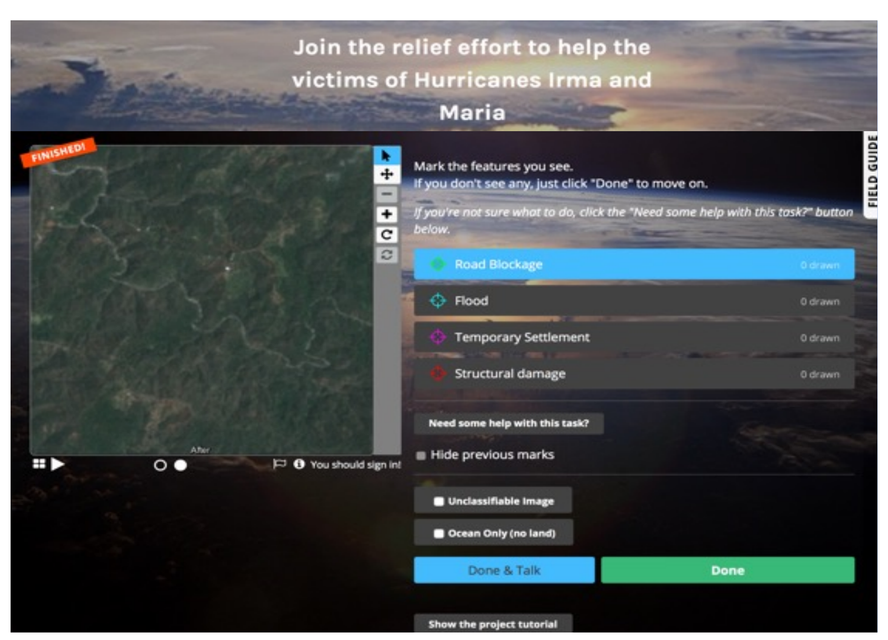
Motivation for using point marks

- Existing large satellite image datasets for building damage detection: SpaceNet, XView.
- But still need to fine-tune models on new data for the current disaster response operation.
- This new data needs to be annotated and pre-processed in a short period of time during the disaster.

Volunteer marks are useful, but require additional processing, as they often contradict to each

Planetary Response Network

RescueGlobal Zooniverse



Contributions: the processing pipeline

The processing pipeline to create a training dataset from point crowdsourced marks to train an object detection algorithm for damage mapping.

Crowd-labelled Dataset

Satellite images

- MAXAR Open Data program: satellite images before and after the disaster.
- Caribbean islands Antigua and Barbuda.

Volunteer marks

Zooniverse platform: volunteers marked the points on images with structural damage of different severity.

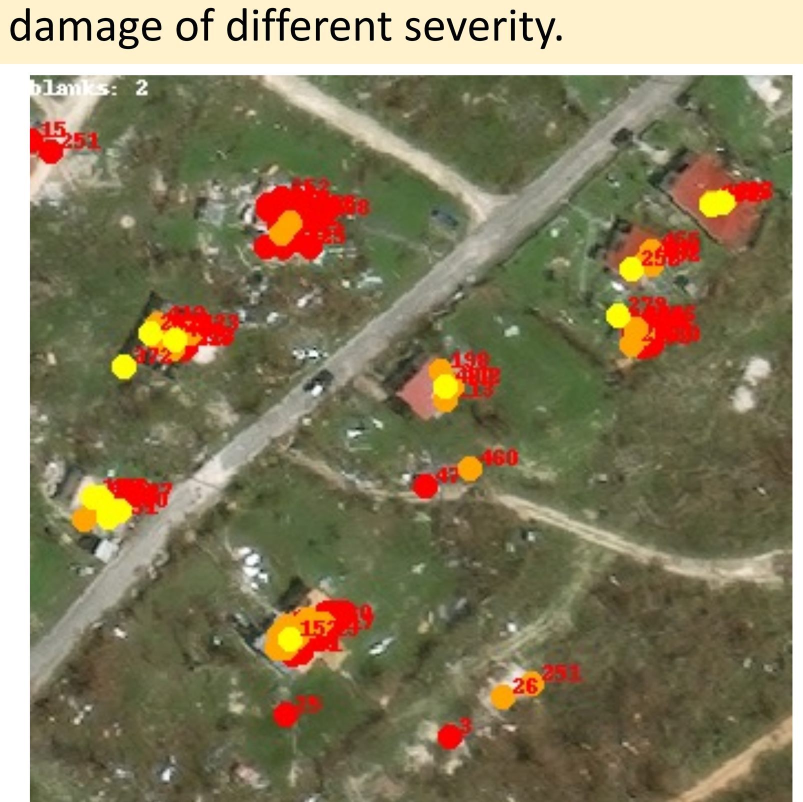
This data needs to be converted to the input suitable for computer vision algorithms.

Problems

1. Point marks instead of object shapes;
2. Lack of consensus for nearby marks.

Solution

1. Detecting the building footprints;
2. Aggregating marks inside the buildings.



- Minor damage
- Significant damage
- Catastrophic damage

Building Footprint Detection Network

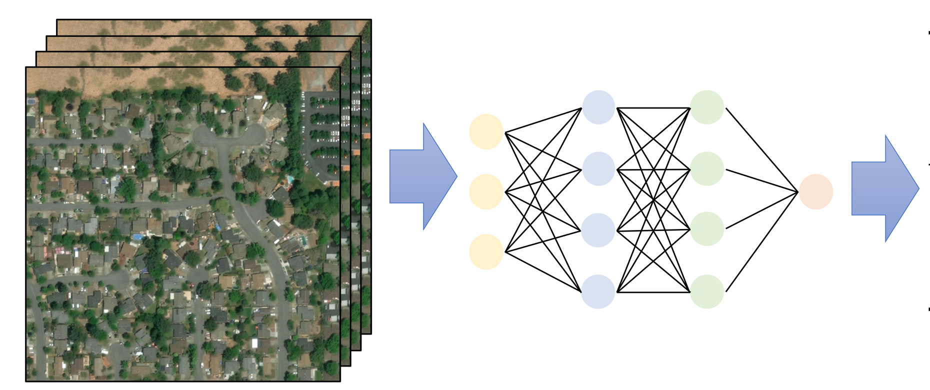
Why object detection, not segmentation

1. A lot of pre-processing work to obtain and co-align multitemporal satellite images pixel-by-pixel, and for object detection we generally need less precision when defining footprints.

2. We don't actually require the precise pixel-by-pixel outputs, we rather need the amount of damaged buildings and the level of their damage in the particular area for disaster relief purposes.

Architecture

- Ensemble of UNet meta-architectures pre-trained on XView2, similar to one of the winning solutions for this challenge.
- Convert the segmentation masks into bounding boxes.



XView2 dataset

github.com/DIUx-xView/xView2_first_place

Timestamp	AP50	F1	Precision	Recall
Pre-event	38	57	52	63
Post-event	23	47	44	49

Mark Aggregation Algorithms

Aggregate marks inside each building footprint: find a consensus label for this building.

Majority voting

- For each object the most common label is selected
- When the data quality is low, a significant number of volunteers can miss damaged objects and leave them unmarked
- Weighted labels, with a lower value for the undamaged label
- Optimal weight varies in different cases

Bayesian classifier combination

- Learn the accuracy of each label class for each volunteer
- Weight their labels accordingly

Majority voting Bayesian classifier combination

F1 score accuracy results

Label	MV	BCC
average	90	**92**
undamaged	70	**92**
minor	40	40
significant	**60**	58
catastrophic	59	**65**

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Damage Detection Example

- Post-event images only
- Faster-RCNN pre-trained on ImageNet.

Accuracy results

AP	18.5
AP50	31.2
AP75	21.9
APs	16.2
APm	27.2
APl	0.0

Ground truth Predictions

Conclusions

- A crowdsourced point-based labelling strategy that reduces the time to create damage datasets.
- We rely on only point marks placed anywhere on damaged buildings.
- This allows us to employ non-expert volunteers and to speed up the labelling process.
- Datasets can be used to train a neural network for damage detection with the sound accuracy.
- This network can then be used during the same response deployment.