

Research Proposal for Building damage and recovery evaluation for Beirut explosion

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Introduction and background

Shortly after 18pm on August 4 2020, the roof of a warehouse at the Port of Beirut caught alight and there was a large initial explosion. About 30 seconds later, there was a colossal explosion that sent a mushroom cloud into the air and a supersonic blast wave radiating through the city. That blast wave leveled buildings near the port and caused at least 200 deaths, 3 reported missing, 6,500 injuries, US\$10–15 billion in property damage, and leaving an estimated 300,000 people homeless. Inexpensive, rapid, and accurate assessment of the damage and recovery levels for disasters such as Beirut explosion. It can also provide essential information in implementing emergency response plans, facilitate better estimates of areas at risk of high damage and casualties, and will provide policy makers and public with more accurate information about the event[1]. However, reliable data usually remain scarce in the developing world, hampering efforts to assess damage and recovery levels. In this proposal, we are aiming to develop an accurate, inexpensive, and scalable method for estimating damage and recovery levels after disaster from high-resolution satellite imagery. Using survey and satellite data from Beirut before and after explosion from publicly available data, we plan to train a convolutional neural network to identify image features that can explain majority of variation in damage and recovery levels.

Literature Review

Satellite remote sensing technology provides qualitative and quantitative opportunities in the context of varied functions such as assessing post-disaster damage, responding through operational assistance[2-4], and risk reduction. The most remarkable contribution of remote sensing imagery is post-disaster damage assessment[5].

The post-disaster recovery phase relates to the period after which initial relief has been provided and is characterized by efforts directed at bringing back normalcy in people's lives and improving the overall circumstances. The major data source for post-disaster recovery monitoring is remote sensing data, including satellite and aerial imagery. Based on change detection from multi-temporal remote sensing data, needs for reconstruction around damaged areas can be detected and monitored. The methodology of change detection is similar in comparison to damage assessment. For example, de Alwis Pitts and So [16] utilized an object-based change detection mechanism to identify the changes before and after two earthquake events; the Van earthquake in eastern Turkey in 2011 and the Kashmir earthquake in northwest Pakistan in 2005. They used high resolution satellite imagery, including the WorldView-2 (0.46 m for panchromatic band and 1.85 m for multispectral band), the Geoeye-1 (0.41 m for panchromatic band and 1.65 m for multispectral band), and the Quickbird-2 (2.44 m for spectral and 0.61 for panchromatic band). Pre- and post-disaster imagery was acquired and road information was obtained from openStreetMap. The changes in edges, texture, and gradient of primary roads were calculated, and changes of open green spaces were also detected. It became apparent that the quantified information contributed to the observation of disaster recovery over time. Contreras et al. [17] reported the progress of recovery efforts after the earthquake at L'Aquila, Italy in 2009. The recovery evaluation was based on remote sensing and ground observations. They used QuickBird imagery to detect the progress during the recovery process from damaged buildings. Spatial indicators were used to

determine the progress of the recovery in L'Aquila by 2010, 2012, 2014 and 2016. Yan et al. [18] utilized geotagged Flickr photos to monitor and assess post-disaster tourism recovery after the Philippines earthquake and Typhoon Haiyan in 2013. Geotagged Flickr photos were analyzed through quality enhancement (both locational accuracy and thematic accuracy), and quantitative and qualitative investigation of the available visual contents. Results showed spatiotemporal patterns of the recovery status and trends[6]. NASA's Advanced Rapid Imaging and Analysis (ARIA) team used satellite-derived synthetic aperture radar data to map the likely extent of damage as preliminary damage estimation. However, little recovery evaluation has been done using deep learning technique to analyze satellite images.

Researchers predicting economic activity, a very important factor to estimate disaster recovery, from satellite images are currently using deep learning techniques. A popular recent approach leverages satellite images of luminosity at night ("nightlights") to estimate economic activity[7-10]. While this particular technique has shown promise in improving existing country-level economic production statistics [7, 10], it appears less capable of distinguishing differences in economic activity in areas with populations living near and below the international poverty line (\$1.90 per capita per day) and doesn't utilize the rich information from nightlight images. Thus, Jean et al. [19] developed a model utilizing daytime images to estimate consumption or assets as index for economic activity. And the model's predictive power declines only modestly when a model trained in one of their sample countries is used to estimate economic activity in another country.

However, little research has been done for Beirut explosion recovery analysis using deep learning technique from satellite imagery. Having monthly cloud-free satellite imagery with stray-light correction from Earth Observation Group, we aim to build a model that predicts disaster recovery using both nightlight and daytime images to evaluate disaster recovery for Beirut explosion from time to time.

Data collection

Earth Observation has monthly satellite image data available and we are going to submit a proposal for the access of their data. Data from Open Map Lebanon may also be used for damage assessment since volunteers have taken many ground photos for damaged buildings affected by Beirut explosion. Continuous satellite image from Earth Online might also be used in the future.

Methodology

Recovery goes beyond the reconstruction of buildings and infrastructure, as it implies the rebuilding of people's lives and livelihoods [12]. Rather than a strictly defined phase, it is more context and location specific, defined by the actions of the affected community. Brown et al. [13] identify six sectors that need to be considered when evaluating the recovery process, namely, transport, building/shelter, transitional shelters and IDPs, services, environment, and livelihoods. Considering that all these factors might be very hard for CNN model to learn and avoid overfitting in a relative small dataset for validation, we make the assumption that nightlight intensity and features extracted from daytime images can represent recovery level. Our model will only using nightlight intensity and the relationship of daytime image and nightlight intensity as label for disaster recovery. To determine this relationship, daytime and nightlight images of the same area in Lebanon will be collected as training set and nightlight intensities will be divided into three classes: low, medium, and high at 1km

resolution. Then, we plan to use our fine-tuned CNN model to estimate nighttime light intensity at various locations given the corresponding daytime satellite images.

Steps for recovery evaluation model using lightness intensity:

1. Start with a convolutional neural network (CNN) model that has been pretrained on ImageNet.
2. Fine-tune the CNN model using Demographic and Health Surveys (DHS) data such as Lebanon Economic Data cross-validation, output accuracy and training it to predict the recovery from nighttime light intensities after explosion.
3. Use model on step 2 as a feature extractor for daytime satellite images to build a new model by discarding the last layer of the CNN model, which is the nighttime light classification layer. Then train it via DHS data, output accuracy and predict the recovery from daytime images after explosion.
4. Compare and combine models in step 2 and 3.
5. Predict Beirut explosion recovery from time to time using satellite imagery.

Without the assumption above, we can also build model using similar approach as Diana et al (2017)[15]:

Steps for another recovery evaluation model:

1. Start with a convolutional neural network (CNN) model that has been pretrained on ImageNet.
2. Identify sectors that need to be considered when evaluating the recovery process, such as transport, building/shelter, transitional shelters, etc..
3. Assign weights for each sector and formulate a recovery index.
4. Use CNN model to identify categories of buildings in each image from satellite imagery and calculate recovery index from time to time.
5. Assess Beirut explosion disaster recovery according to recovery index.

Significance

The above mentioned CNN model using public available satellite imagery data can provide inexpensive, rapid, and accurate assessment of the damage and recovery levels for Beirut explosion. It can also provide essential information in implementing emergency response plans, facilitate better estimates of areas at risk of high damage and casualties, and will provide policy makers and public with more accurate information about the event[1].

Moreover, this model could have broad application across many scientific domains and may be immediately useful for inexpensively assessing recovery after other disasters such as Wildfire, flood and earthquake.

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