Post-disaster recovery assessment using multi-temporal satellite images with a deep learning approach

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Abstract
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Abstract

Natural disasters cause massive problems for affected communities, societies, and economies, with devastating impacts on infrastructure, business sectors, and people in the affected region. Recovery starts after the immediate post-disaster response phase, mainly search and rescue operations, have concluded. Compared to the relatively short-lived response phase recovery can then take years or even decades, and is the most poorly understood phase of the disaster management cycle. It comprises reconstruction of buildings, which is easier to detect using direct physical assessments, as well as recovery of the functions of the affected area, such as schools and factories, which are harder to detect and usually are approached using proxies. Remote sensing (RS) as an effective and rapid tool for monitoring large areas is essential to acquire geospatial data. RS techniques have been extensively used for different aspects of the Disaster risk management (DRM), from quantification of vulnerability to rapid damage assessments, and numerous image analysis methods have been developed. Conversely, the recovery phase has seen very little research. Most of the existing studies have been mainly making use of manual information extraction or have used comparatively outdated image processing techniques. The final recovery assessment is usually done via change analysis of the extracted multi-temporal information.

Recently developed deep learning methods, in particular, convolutional neural network (CNN), tend to outperform existing RS data processing methods. Recent studies have already demonstrated the efficiency of deep learning approaches in extracting damaged areas from satellite and aerial images. However, those studies employ mono-temporal RS data, detecting damaged areas from the images acquired immediately after a disaster. In addition, deep learning approaches have not yet been adequately assessed for multi-temporal image analysis in computer vision researches, and no connection to recovery assessment has been made yet. In this study, we develop a new patch generation model that concatenates multi-temporal satellite images from before the disaster, right after the event, and later post-disaster images to be used as input for deep learning approaches (Figure 1). The concatenation is done by vertically and horizontally merging the equal size initial patches that belong to the same area in one patch/image rather than concatenating images as different bands. Then, the final patches for each area are used as training samples in the deep learning approach. In this study, a CNN approach with fully connected layers and backboned by VGG-16 is used to classify the images into recovered or not-recovered areas. The developed model was tested for recovery assessment in Tacloban, the Philippines, which was hit by Typhoon Haiyan in 2013. Very high-resolution (Pansharpened/0.5 m) satellite images

acquired from different platforms (e.g., Pleiades, Geoeye and Worldview2) were employed to generate the training samples. Since it is even visually hard to determine the recovered or not-recovered areas by comparing the multi-temporal satellite images, the training areas that their recovery ratios have been visually determined less than fifty percent were selected as not recovered samples and the rest including not-changed ones were considered as recovered. A total of 989 training samples were generated, and 10% of them were randomly selected to conduct the accuracy assessment. The developed model produced 89% accuracy in distinguishing the test data/images to recovered and not-recovered classes.

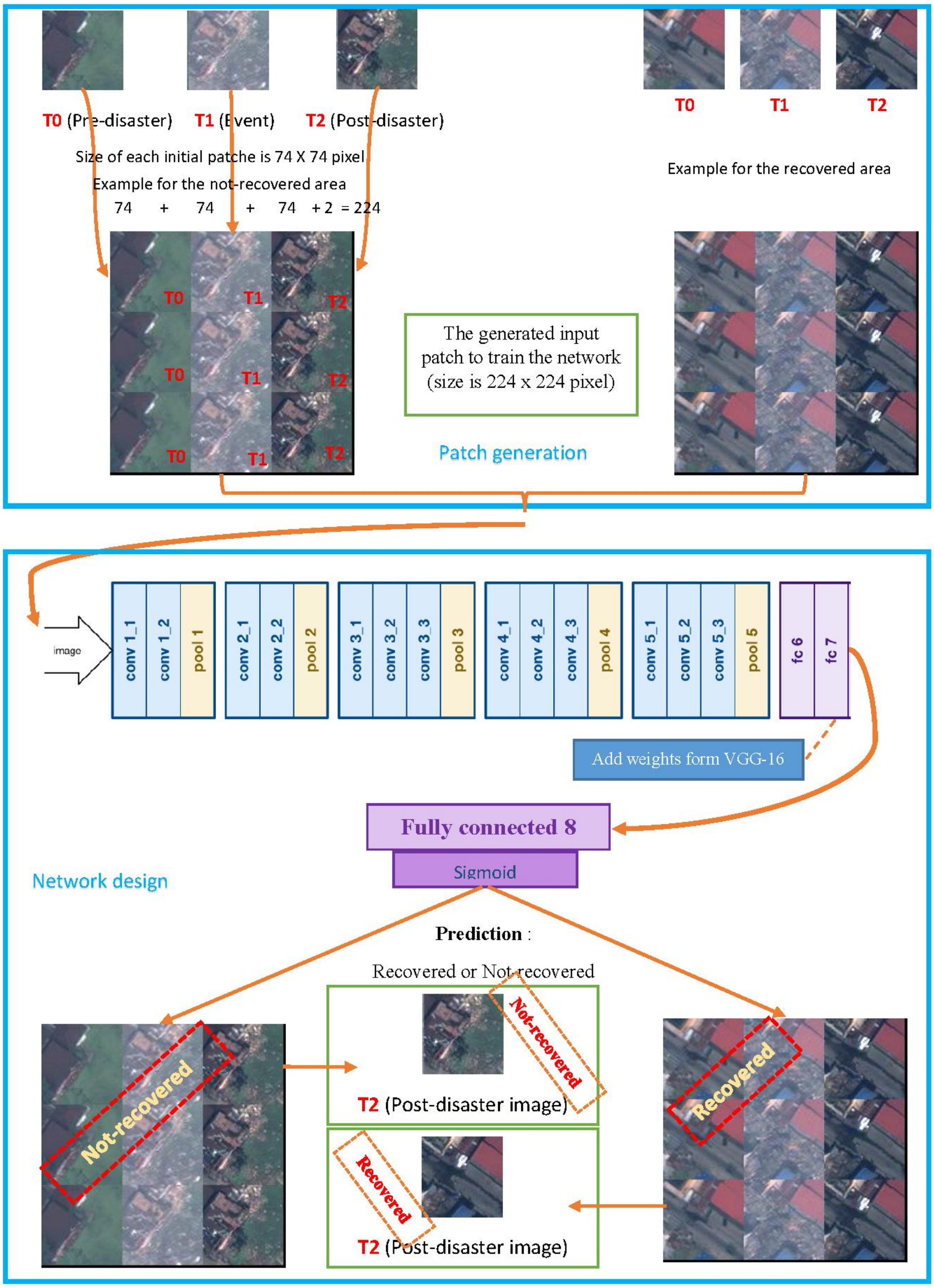

Figure 1. The developed deep learning approach for post-disaster recovery assessment from multi-temporal satellite images.