Rapid safety evaluation of buildings after earthquakes using drones and machine learning

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ABSTRACT

Completing safety evaluations of buildings is critical for the health and safety of a city's community following a damaging earthquake. Most contemporary post-earthquake evaluations involve groups of people who physically inspect buildings, most often without training specific to evaluating earthquake damage. Three main problems arise from this practice: i) the inspectors are at risk, ii) the results are varied, subjective, and often contradictory, and iii) the process can take a long time to be completed. The use of drones is becoming more common for the inspection of buildings, bridges, and hard-to-reach locations and infrastructure. However, these drones must be piloted individually, and the data that is collected by these means need to be assessed by experienced engineers, often in a piecemeal manner. While the first problem of having people at risk can now be partially solved, the second and third issues of subjective results and long delays remain even with contemporary drone usage. We present a summary of a proposed framework and progress on the use of a swarm of drones working autonomously and collaboratively to rapidly collect images of post-earthquake buildings and assess them. The reported exercise to date has focused on a group of buildings within a contained space. A review of current machine learning techniques for damage identification, localization, and quantification is also presented, highlighting the research needs for future improvements.

1 INTRODUCTION

The post-earthquake damage and safety assessment of buildings is typically undertaken by volunteers, frequently engineers and architects. The objective of the building assessment is to qualitatively establish the usability of buildings and to inform the public about the safety of using each building. However, the product of such assessments typically does not include an exhaustive nor precise engineering assessment of the state of the building and all of its components (Ministry of Business Innovation and Employment (MBIE) - Hikina Whakatutukī, 2015). Some buildings in Aotearoa have been instrumented for structural health monitoring purposes, which can provide additional data to inform the post-earthquake inspection process. However, at this stage the investment needed per building both in terms of equipment and interpretation precludes this solution from being widely implemented. Other city-wide solutions have also been implemented, where a large density of free-field monitoring equipment is used to better inform the shaking demands at each building location. MBIE – Hīkina Whakatutukī (2015) published a field guide for the successful completion of post-earthquake building assessments in 2015, largely based on previous documents prepared by the New Zealand Society of Earthquake Engineering (NZSEE) (2009) and the Applied Technology Council's (ATC) (2005). The MBIE – Hīkina Whakatutukī (2015) guide was revised and improved to take into consideration the learned experience from the 2010–2011 Canterbury earthquakes, but the basic framework of the procedure remained the same as in the referenced preceding guidelines as follows:

- A team of volunteers (typically engineers or architects) visually inspects the building, often only from the exterior of the building, spending about 20 minutes per building.
- The inspectors then complete a form that contains data on the inspector and the building, and provides information on the building damage observed based on a series of vulnerable components that could be hazardous to people occupying the people in the near future. Examples of vulnerable component classifications include structural elements such as the foundation and the roof as well as non-structural elements such as cladding, parapets, and chimneys. The damage can be classified as minor/none, moderate, and severe.
- Upon completion of the inspection, the assessor recommends an assessment outcome and installs a placard on the building of a colour corresponding to the following observed damage levels: i) white (or green) represents no or little damage to the structure, ii) yellow represents moderate damage and restricted access either to some part(s) of the building or for a certain time period, and iii) red represents heavy damage and that entry is prohibited.

Approximately 26% of the buildings in the Christchurch CBD were given a red or yellow placard after the September 2010 Darfield earthquake (Stevenson et al., 2012), with the rate of placarding increasing to 24%, 23% and 53% for red, yellow and green placards respectively after the February 2011 Christchurch earthquake (Weng Yuen Kam & Pampanin, 2011). Due to the superficial and rapid assessment methodology involved, placarding does not seem to be a good predictive tool of the future usability of the building, with several green and yellow placarded buildings being demolished after the Canterbury earthquakes, and demolitions typically occurring after minor or moderate damage was marked in the building inspection form (Marquis, Kim, Elwood, & Chang, 2017). The placarding system currently in place is probably "*the best-available indicator of observed damage in a systematic [sic] and fast"* way (Weng Y Kam, Pampanin, & Elwood, 2011), but significant improvements are needed to improve the current system's accuracy and efficiency. The most necessary improvements emerge from three main issues arising from the placard system. The first issue relates to the risk to inspectors, who walk around the buildings and sometimes inside them, with the subsequent risk associated with falling building elements, unstable ground conditions, debris, and earthquake aftershocks. The second issue is related to the subjectivity and variability of reporting observed damage as minor, moderate, or severe, even with established guidelines to follow. This subjectivity is related to the experience of the assessor and to their risk tolerance, as well as the chance associated with observing or not observing particular elements of a building. The third issue is related to the extended duration of time that it takes to complete building assessments at a city-wide scale.

The risk for the inspectors can be significantly mitigated by using teleoperated devices for inspection such as drones. For example, numerous studies have used Unmanned Aerial Vehicles (UAVs) for automated building inspection procedures (Rakha & Gorodetsky, 2018) using simple or sophisticated teleoperation interfaces (Teixeira, Ferreira, Santos, & Teichrieb, 2014). However, drones still need to be piloted by a qualified person and the data still need to be analysed by experienced engineers. Thus, drones may improve the safety of the assessments, but they do not reduce significantly the time overhead and the number of experts required.

The proposed framework will enable a rapid, autonomous safety evaluation of buildings, to be completed within 24 to 48 hours after an earthquake using drone swarms and machine learning techniques. Herein, the progress to date and plans for the near future are summarised but, more importantly, the authors are using this medium to offer collaborative opportunities for industry experts, academics, and stakeholders (e.g., councils).

2 METHODOLOGIES

The framework for the fully automated post-earthquake building assessment methodology that relies on the efficient city-wide coordination of a drone swarm is illustrated in Figure 1. The framework fuses pre-event data with real-time data collected by a drone swarm to automatically and efficiently complete reliable building assessments, while facilitating a seamless collaboration with engineers. Pre-event data (e.g. Geographic Information System (GIS), Building Information Models (BIM), historical inspection data) can enrich the unknown environments (e.g. location, geometry, materials of building roof). The drone swarm can intelligently analyse pre-event data to plan and optimise inspection missions, enhancing autonomous navigation and improving damage detection efficiency. The fusion of pre-event and post-event real-time data can be synthesised to understand a building holistically and reliably and to inform engineering decisions. The framework results in automated assessments for each building in relation to damage level, cordoning/occupancy, and need of further inspection.

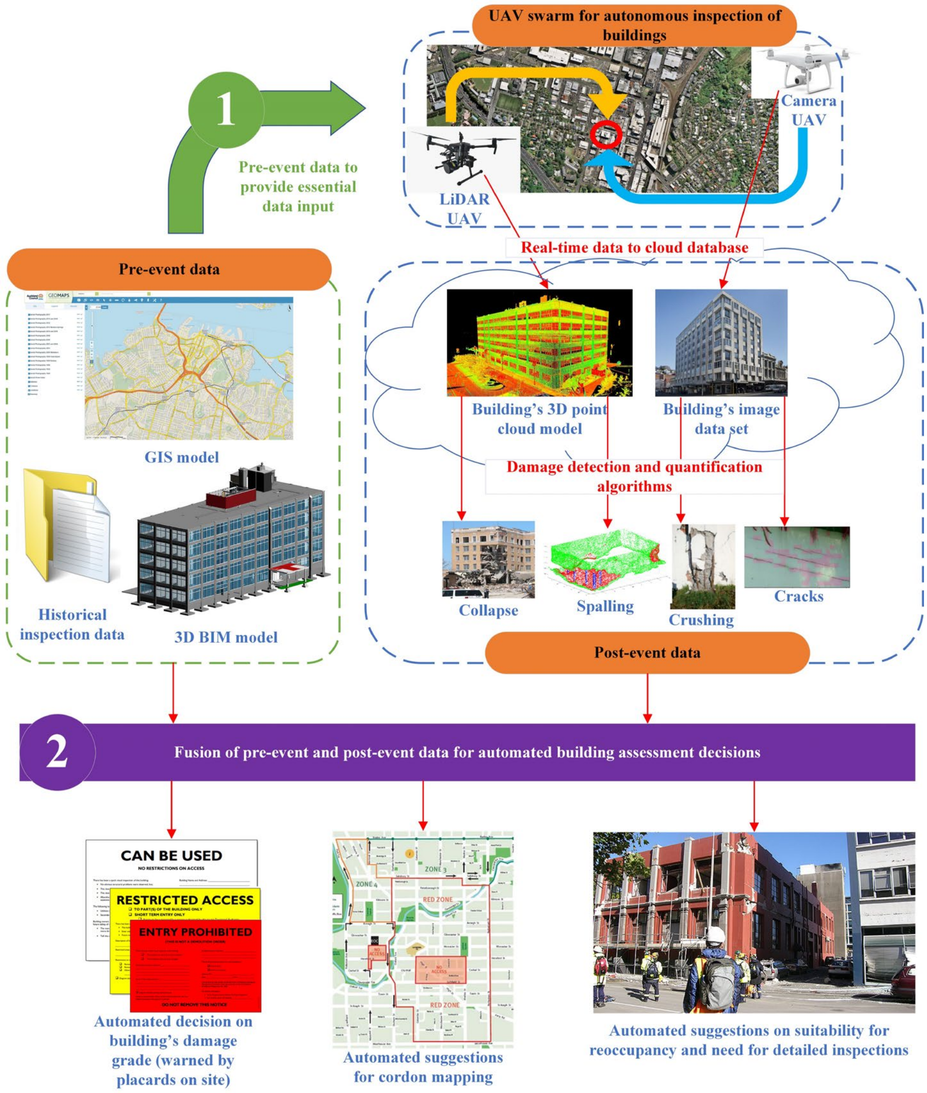


Figure 1: Proposed framework for post-earthquake automatic data collection and building assessment.

2.1 3D BIM modelling

Research on computer-aided building design has focused on the development of 3D semantic object-based building models, known as BIM (Borrmann & ErnstRank, 2009). These efforts have resulted in the ISO-16739 Industry Foundation Classes (IFC) open BIM Standard, a common language to share open BIM data. IFC enables the sharing of physical and functional representations of a building throughout its entire life cycle. BIM has the potential to facilitate construction automation by maximising the collaborative opportunities provided by the open BIM standard (Eastman, Jeong, Sacks, & Kaner, 2010). BIM and GIS can provide accurate description on 3D structures and its surroundings to assist the generation of UAV inspection missions and improve UAV autonomous flights. Additionally, BIM is an open, neural data model that has the potential to visualise structural damage and be integrated with damage data, which can be used to automate safety assessment and the establishment of structural analysis models.

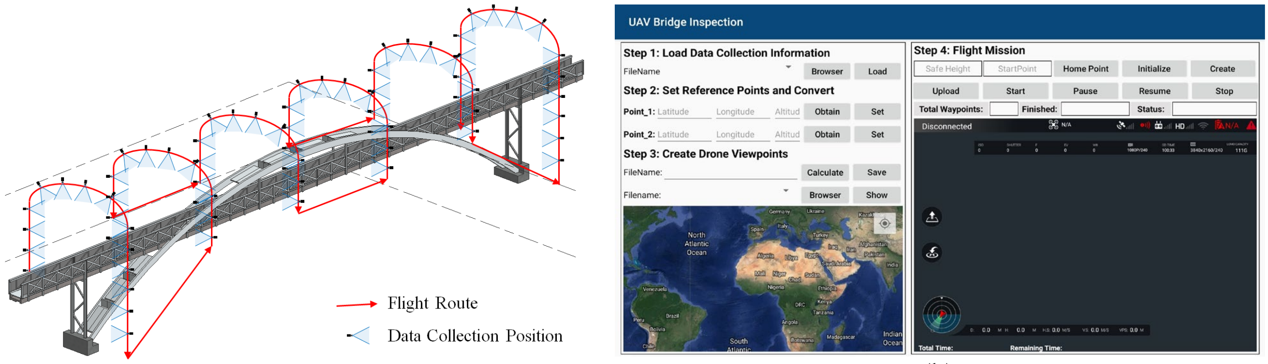
2.2 Swarm of drones for data collection

The proposed system employs drones to quickly collect necessary data during post-earthquake inspection operations for damage detection, localization, and quantification. The commonly used data for damage detection includes RGB images/video, point clouds, and thermal images (Rakha & Gorodetsky, 2018; Teixeira et al., 2014). The optical images/videos by the UAV are used most preferably to detect building damage due to the low cost and high convenience in the early hours after the disaster (Nex, Duarte, Steenbee, & Kerle, 2019). The LiDAR sensor can directly obtain position and precise elevation information in the form of 3D point clouds under most weather conditions, which has greater potential to detect severely damaged buildings (e.g., story-collapsed) (Xiu et al., 2020). By applying the infrared thermal imaging technology, the temperature distribution of the building's external wall can be determined by analysing the radiation energy to detect cracks and eliminate hidden dangers after the disaster (Zhang et al., 2020). The current state-of-the-art research on damage detection, localization and quantification is described in detail in the next section.

The authors have identified two main issues with the use of drones to collect data for safety evaluation of buildings: i) a human agent needs to pilot each individual drone, resulting in a time-consuming, labour intensive process that yields low quality and often inconsistent data, and ii) the use of a single drone or a small number of drones does not speed up the assessment process when compared to the manual, labour-intensive inspection by humans. To solve these two issues, we propose a new framework for UAV based inspection and assessment process that utilizes a swarm of drones, working both autonomously and collaboratively as well as in synergy with the human agents (e.g. search and rescue services). The coordination of the motion of the swarm of drones will rely on sophisticated path planning and control techniques. Appropriate interfaces will also be developed for efficient human drone interaction and collaboration. Current drone technologies are able to fly in almost any weather environment, and if the drones are equipped with LiDAR they can also fly at night. A current regulatory issue is the strict constraints within which drones can fly in urban areas, especially when there are airports and aerodromes nearby. We are collaborating with several councils and regional authorities to reduce the perception of risk that drones pose to people and the Public Policy Institute within the University of Auckland is helping to understand how the constraints could be lifted and/or reduced during an emergency.

The pre-event geo-referenced 3D BIM model will be used as data input for automatically generating UAV flight missions, that will be executed in an autonomous manner by a swarm of simultaneously coordinated drones. The pre-event integrated GIS and BIM model will be utilised to provide geometry and geographical information of the target scenarios for UAV inspection mission planning. To ensure the effectiveness of UAV-captured data, the data collection positions should be identified and adjusted based on the real buildings and geographical information so as to guarantee full coverage of all the target buildings of interest. It is also critical that the UAV inspection mission satisfies the constraints imposed by flight safety requirements, no fly zones, and UAV's limited battery life (Hamledari, Sajedi, McCabe, & Discher, 2021). To minimize the data acquisition time, both the UAV inspection mission planning and the mission execution will be automated. Commercial software such as Pix4D Capture can assist to create simple flight mission like polygon, grid, or circular plan for land surveys, but the capability to fly around objects has not been fully developed in commercial packages. The data collection positions and tasks can be transferred as a pre-programmed flightpath to be automatically executed by the UAV, but such types of UAV flight mission control applications have not been developed yet. As part of our current efforts, a Revit Plug-in or Add-on to plan UAV inspection missions for bridges by invoking the bridge BIM model and a mobile application to control the UAV for autonomous data collection have been developed, as shown in Figure 2.

It is evident that the aforementioned commercially available packages for flight control of UAVs do not offer the required dexterity for planning complex missions involving multiple buildings or for coordinating the motion of multiple UAVs of a swarm. Planning the motion of a swarm requires sophisticated methods for leader-follower control and path planning, fleet coordination in a synergistic manner, and real-time obstacle avoidance. Thus, it is of paramount important to develop new control and path planning algorithms that will facilitate the successful completion of post-earthquake building inspection missions by the swarm of UAVs.



(a) (b)

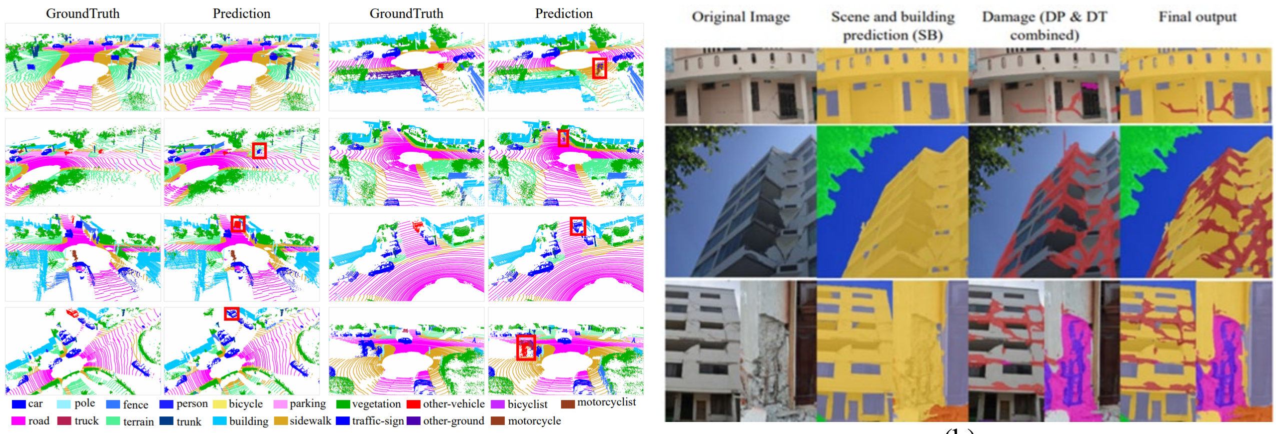
Figure 2: Developments on automatic flight path showing a) proposed flight path, and b) developed app

2.3 Damage detection, localisation and quantification

As previously described, drones have shown great potential to automatically acquire high-quality inspection data such as images and point cloud data (PCD) after earthquakes (Velev, Zlateva, Steshina, & Petukhov, 2019). Data analysis currently involves manual processes dependent on empirical knowledge, which result in time-consuming and labour-intensive processes, especially as the amount of data from large-scale regions increases. We need to solve three different challenges to facilitate the automated data analysis and to ensure seamless merging with current practices. These challenges are: i) automated damage detection, ii) automated damage localization, and iii) automated damage quantification.

The first need to develop automated damage detection is to classify post-earthquake buildings as totally collapsed, partially collapsed, or damaged. This initial building assessment will use PCD, but there is no existing automated seismic damage detection method based on PCD using deep learning technique (Janalipour & Mohammadzadeh, 2019). PointNet (Qi, Su, Mo, & Guibas, 2017) is the first deep learning network for processing PCD, and its efficiency has already been tested to classify ground, vegetation and buildings from an aerial point cloud (Zhongyang, Yinglei, Xiaosong, Xianxiang, & Li, 2018) as well as construction infrastructure such as tunnels and railways (Rodríguez, Lindenbergh, Riveiro Rodríguez, & Sánchez Rodríguez, 2019). Figure 3(a) shows an example of another algorithm for automated classification of point clouds – RandLA-Net. We are currently testing the efficiency of PointNet for semantic segmentation of bridges, and we will then expand it to building structures. The second aim for automatic damage detection comes after the buildings have been classified using PCD. The buildings classified as damaged buildings will be further studied using imagery data to detect and classify main seismic damage such as cracking, spalling, and exposed rebars for a more detailed building assessment.

Two-dimensional convolutional neural network (2D CNN) is a deep learning technique for damage detection in terms of performance and accuracy (Cha, Choi, & Büyüköztürk, 2017; Kang, Benipal, Gopal, & Cha, 2020). Figure 3(b) presents an example of the seismic damage detection results using this deep learning technique. However, these methods only focused on detecting defects from a single image, and little research has been conducted on seismic damage detection for a whole building or a group of buildings. Thus, future work will focus on developing seismic damage detection methods using the object detection algorithms, but applicable to a considerable number of images with multiple types of defects captured from a group of buildings.



(a) (b)

Figure 3: (a) RandLA-Net classification of point clouds (Hu et al., 2020)*, and (b) Detection results for multiple types of seismic damage* (Hoskere, Narazaki, Hoang, & Spencer Jr, 2018)

The objective of damage location is to associate identified damage with corresponding individual buildings and to assign that damage to specific structural elements. Images typically lack context information, making it difficult to identify damage location on a specific building and a structural element based only on those images. Thus, none of the image-based damage detection techniques provides the damage location relative to the inspected structure (Isailović et al., 2020). Previous research attempted to solve this challenge by integrating a GIS model (Xiong, Li, & Lu, 2020), but the GIS model is not always available for all regions, limiting its application. In response to this challenge, a data fusion method is proposed to integrate the captured images with the corresponding point clouds, linking the two sets of data together.

The objective of damage quantification is to measure the magnitude of the damage caused by the earthquake, firstly using point cloud data to measure building deformation and secondly using images for surface damage measurement. This process aims to improve visual inspection methods through quantitative analysis and objective damage severity classification. We will first utilize advanced point cloud processing techniques to measure building deformation and displacements. Current image-based defect quantification methods are limited to pixel units, which lacks meaning in real-world dimensions. A data fusion method will be proposed to generate 3D defect maps, which can then be translated to real world maps using real units (e.g., mm). Damage quantification can also highlight risk or hazards before they evolve into collapse.

2.4 Automatic safety evaluation

The automatic safety evaluation process will initially be based on the categorization already embedded in the MBIE document (2015). The damage automatically identified by the machine learning methods using the imagery data collected by the drones can be automatically classified as minor, moderate, and severe and assigned to a structural element such as beams, walls, etc. External non-structural elements such as parapets or cladding can also be assessed. As we progress with the project, further complexity can be built into the system to perform quick structural analysis based on the observed damage. As an example, an estimation of the residual capacity of columns based on the number of cracks and their width might be feasible in the near future. Other parameters not related to the building itself can also be incorporated into the evaluation in addition to the building properties such as size and height/number of storeys. For example, a modifier can be added in the evaluation score if the building's safety can compromise other buildings, or if the building is close to a main road or facility (e.g. hospitals). The plans for this stage are still developing pending the resolution of several significant technical issues such as automatic damage detection and quantification.

3 CONCLUDING REMARKS

In conclusion, the authors are working toward a framework that will enable a faster, safer, more consistent and objective, automated safety evaluation of buildings after an earthquake. The framework relies heavily on a swarm of drones to collect the data using mainly Lidar and RGB cameras, with the drones working collectively and in synergy with human agents. The authors have identified several challenges and are working toward solutions. We are open to collaboration with industry partners and with key stakeholders such as local council and territorial authorities.

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