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Remote Sensing And Machine Learning For Enhanced Post-Disaster Response: Insights From The 2023 Türkiye–Syria Earthquake

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ABSTRACT

The 2023 Türkiye–Syria earthquake caused widespread devastation with thousands of fatalities. This study aims to investigate the potential of remote-sensing methods in improving post-disaster response efforts, by leveraging advanced technologies such as satellite and aerial imagery with geospatial data, computer vision, and machine learning. These techniques include change detection through satellite image analysis, regional damage assessment, optimal path planning for multiple unmanned aerial vehicles (UAVs), and 3D reconstruction for local damage assessment. The findings of this study highlight the importance of incorporating data science and machine learning into disaster response planning, which can lead to an improved and more efficient allocation of resources, rapid decision-making in crises, and a more effective overall response. The insights generated by this study can inform the development of new disaster management strategies and the design of advanced data science tools, leading to better outcomes for communities affected by natural disasters.

Keywords: Türkiye–Syria earthquake, remote sensing, satellite imaging, change detection, neural radiance fields

INTRODUCTION

On February 6, 2023, two major earthquakes with magnitudes of 7.7 and 7.6 (Mw) struck near southern and central Türkiye and northern regions of Syria, which were the largest in the region since the 1939 Erzincan earthquake. The official death toll had exceeded 57,000, with countless others injured. The twin earthquakes and the aftershocks caused significant damage to the region, resulting in more than a million people being left homeless [1]. This disaster revealed several shortcomings in construction, infrastructure management, and emergency response systems, despite previous experiences with deadly earthquakes, such as the 1999 Gölcük (Marmara) earthquake.

The rapid evaluation of damage to civil infrastructure after a disaster is essential for prompt emergency response and resource allocation [2]. The traditional methods for damage assessment using ground stations are time-consuming and labor-intensive, which cannot be fully automated or scaled without having experts on-site [3]. Furthermore, Reconnaissance after an earthquake has a significant impact on damage assessment, locating survivors, preventing secondary hazards, accelerating the recovery process, and gathering experience about the event [4]. However, current paradigms for reconnaissance are labor-intensive and slow, because, in the early stages of the recovery, human resources are often involved in other urgent priorities. In addition, manual methods for surveillance can cause further risks for the teams gathering data from inaccessible or hazardous locations. Hence, automated reconnaissance provides a more efficient, accurate, and safe way to assess damage and collect data. Data science can make this process automated with the use of algorithms to analyze data and develop tools for effective decision-making.

The recent advances in machine learning (ML) and data science, demonstrated the efficiency of ML-based methods in damage assessments before and after a disaster [5-11]. Since most data-driven damage assessment approaches, require the health state of structures, collecting pre-event data as well as post-event data can enhance the process and provide a baseline for the region of interest [12]. In this regard, remote sensing technologies, such as satellites and unmanned aerial vehicles (UAVs), can be applied for collecting data on structures and infrastructures in their healthy states. The advances in remote-sensing and aerial imagery enabled obtaining high-resolution images within days of a disaster. For instance, the WorldView-2 satellite with 3.7 days can accelerate regional damage assessment using computer vision and AI for generating building footprints as well as damage levels after an event [13]. The prevalent techniques for evaluating building damages with satellite imagery and computer vision are done mainly through two streams, segmentation and classification. Several studies have used convolutional neural networks (CNNs) to develop desired performance levels for them [14, 15]. As a semantic segmentation task for change detection, building damage assessment can be modeled using a CNN-based network that takes in a concatenation of pre- and post-disaster satellite images and outputs the changes. Such models can be followed by damage classification at the pixel level [16]. Although satellite imagery can be applied to assess damage states after an earthquake at a regional level, it may not provide a complete picture of the extent of damage caused by the earthquake. Therefore. UAVs are still necessary to obtain clear images and determine the damage severity. On the other hand, aerial imagery can provide high-resolution close-up images with more details for accurate damage assessments, however, it requires optimal flight path planning to collect data from a region without collision. This is mainly due to the limited flight time of portable UAVs [17].

Metaheuristic algorithms provide an efficient tool for addressing this problem by minimizing overall battery usage, maximizing coverage, and taking into account various constraints, such as preventing no-fly zones, collision avoidance, and limited flight time [18]. Several algorithms have been devised in this regard, which is generally categorized into three main classes: Evolutionary (e.g., GA and CMA-ES [19-22]), Swarm Intelligence (e.g., PSO and WSA [23-26]), and Physics-based (e.g, SA and TEO [27, 28]) the traveling salesman problem algorithms.

Following the recent devastating earthquakes in Türkiye, it was noted that the condition of buildings may significantly change over a short time after an earthquake due to the failure of structural components. For example, severely damaged multi-story buildings collapsed days after the main shock, such as a new six-story building in Malatya. Thus, there is a need to develop novel approaches for continuously collecting data at varying resolutions, taking into account the state of the buildings. To address this issue, a multi-fidelity and multi-level approach can be adopted, which would gather data at different resolutions and over time. Moreover, during earthquakes, people's safety is at risk, making it crucial to develop models that are trustworthy and dependable. For regulatory approval, these models must be explainable, and their predictions must be accurate, ensuring that the model features are sensible. Despite extensive research in the area of data science for damage assessment, only a few models, such as YOLO and NeRF, are suitable for real-world post-disaster applications. Therefore, further investigation is necessary to develop practical outputs, including real-time damage detectors and 3D reconstruction techniques.

METHODOLOGY

Overview of the proposed method

This study proposes a multi-fidelity reconnaissance methodology for a rapid post-disaster response, which is illustrated in Figure 1. As can be seen, firstly the satellite images before and after the earthquake are investigated using specific data-driven models to get a raw estimate of the damaged regions, buildings, and infrastructures. In the second level, the initial route of a UAV or a set of UAVs is determined automatically to get higher-resolution videos of possible damages. An example of paths optimized for a set of four UAVs is shown in Figure 1. In this Figure, the UAVs – shown in distinct colors – start from the starting point and pass the optimal route over the buildings. This problem can be considered a variation of a well-known traveling salesman problem (TSP) in mathematics, where UAVs and buildings represent travelers and cities, respectively.

Recording the data, either the frames extracted from the collected videos or the video files, are directly fed to the classifier machine learning models to perform an initial estimation. This level is necessary in the cases that the satellite images are unavailable or the view is obstructed by clouds or smog. The flight speed in this level is considered high because it is supplementary to the previous level. In the third level, the low-fidelity assessment results of the previous levels besides the available information about the buildings are put together to mathematically model and optimize the flight route of UAVs. It should be noticed that, unlike the previous path planning which provides a coarse assessment, at the final level, the speed and path of UAVs must be tuned for high-fidelity assessments such as 3D reconstructions. Collecting the high-fidelity data, the assessment is performed through machine learning or machine-human collaboration methods.

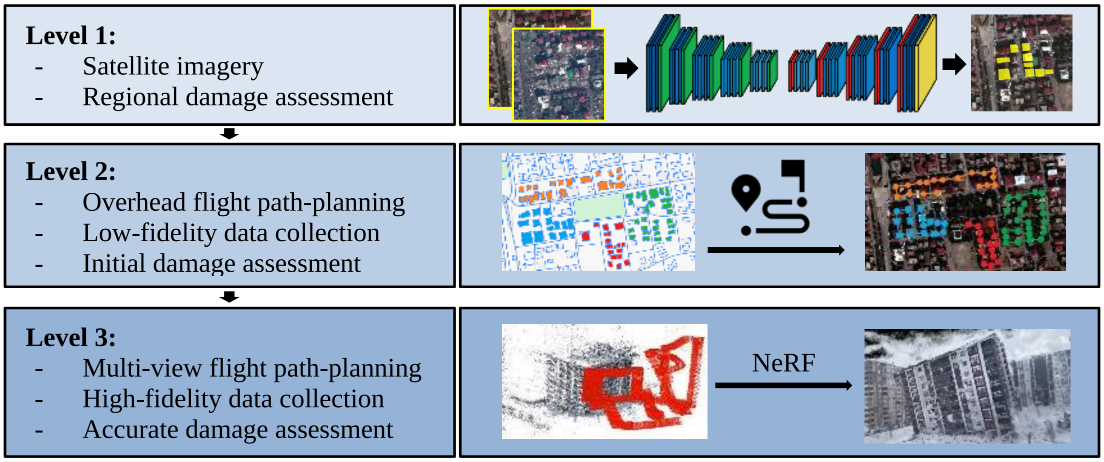


Figure 1. The proposed multi-fidelity reconnaissance methodology.

Level 1: Change detection using satellite imagery

Along with the advancement of machine learning techniques, autonomous approaches for change detection (CD) using satellite imagery have been developed, which can reduce the time and effort required for manual on-ground interpretations [29]. In the context of regional damage assessment, change detection can be used to detect and classify changes in building conditions by comparing the images before and after a disaster, such as earthquakes, floods, and tornados. This approach can provide valuable information for emergency responders and aid organizations to prioritize their efforts and allocate resources more efficiently. Machine learning models such as convolutional neural networks (CNNs) have shown promising results in building damage assessment using satellite imagery for change detection [30]. In this study, a Bitemporal Image Transformer (BIT) model was utilized to detect changes using satellite images before and after a disaster. To maximize the performance of the change detection task, the BIT uses the strength of transformers as well as the CNNs [29].

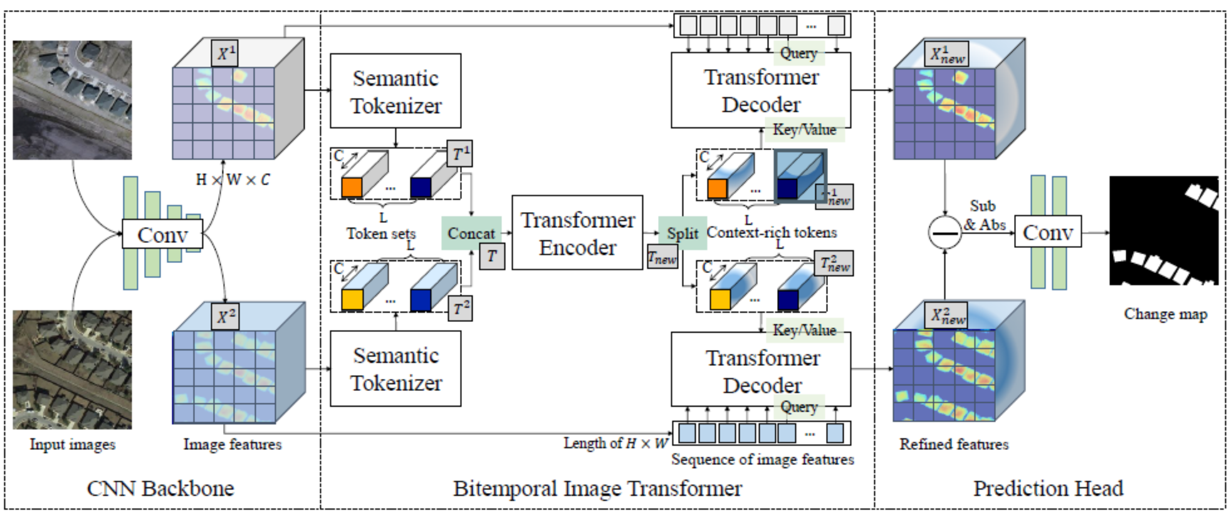


Figure 2. Illustration of the bi-temporal image transformer model [29].

The core component of transformers is the 'attention' mechanism. A transformer is based on two main integral components: 'self-attention' and 'pre-training'. The former allows a transformer model to capture 'long-range' dependencies between sequences of features. A self-attention mechanism tries to estimate the interaction between all n entities of a sequence $X \in \mathbb{R}^{n\times d}$ by encoding them in terms of global information, where d is the embedding dimension (e.g., which damage types would come together in an image from a structure). This can be achieved by first projecting the input sequence $\boldsymbol{X} = (x_1, x_2, \ldots, x_n)$ onto triplet of learnable matrices, Queries $\boldsymbol{W}^Q \in \mathbb{R}^{d_x \times d_q}$, Keys $\boldsymbol{W}^K \in \mathbb{R}^{d\times d_k}$, and Values $\boldsymbol{W}^V \in \mathbb{R}^{d\times d_v}$; and fed into a scale-dot attention mechanism as follows [31]:

$$\boldsymbol{Z} = \text{softmax}\left(\frac{\boldsymbol{QK}^T}{\sqrt{d_q}}\right)\boldsymbol{V} \tag{1}$$

where, $\boldsymbol{Q} = \boldsymbol{X}\boldsymbol{W}^{Q}, \boldsymbol{K} = \boldsymbol{X}\boldsymbol{W}^{K}, \boldsymbol{V} = \boldsymbol{X}\boldsymbol{W}^{V}$, and $\boldsymbol{Z} \in \mathbb{R}^{n \times d_v}$.

Single-head attention mechanism (Figure # (left)) has limitations in encapsulating multiple important relationships at the same time. To tackle this issue, a multi-head self-attention mechanism uses parallel attention layers to project the input onto different representation subspaces with their learnable query, key, and value matrices $\{\boldsymbol{W}^{Q_i}, \boldsymbol{W}^{K_i}, \boldsymbol{W}^{V_i}\}_{i=1}^{h}$. In greater detail, for a given input $\boldsymbol{X}$:

$$\boldsymbol{Q_i} = \boldsymbol{X}\boldsymbol{W}^{Q_i}, \boldsymbol{K_i} = \boldsymbol{X}\boldsymbol{W}^{K_i}, \boldsymbol{V_i} = \boldsymbol{X}\boldsymbol{W}^{V_i} \tag{2}$$

$$\boldsymbol{Z_i} = \text{softmax}\left(\frac{\boldsymbol{Q_i}\boldsymbol{K_i^T}}{\sqrt{d_q}}\right)\boldsymbol{V_i} \tag{3}$$

$$\boldsymbol{Z} = concat(\boldsymbol{Z_0}, \boldsymbol{Z}_1, \dots \boldsymbol{Z}_{h-1})\boldsymbol{W}^{o} \tag{4}$$

where, $\boldsymbol{W^o}$ is the projection weight and $\boldsymbol{W^o} \in \mathbb{R}\hat{}(h.d_v \times d)$

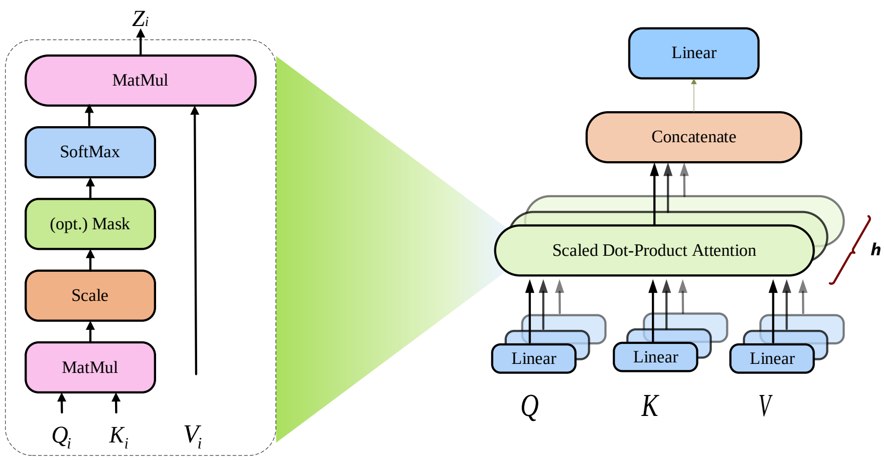


Figure 3. Self-attention mechanisms: Scaled dot-product attention (a) and multi-head attention (b)

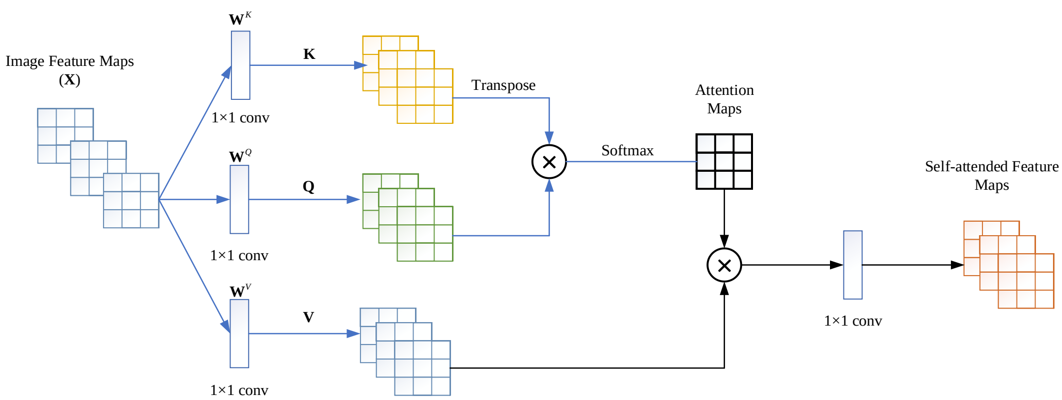


Figure 4. Self-attention mechanism in computer vision [31].

Level 2: Path-planning for UAV

Based on the acquired data from the previous level, the UAV route needs to be determined for autonomous data collection. This problem could be considered a multi-TSP problem, which contains three steps: identifying the region of interest (ROI), clustering the buildings in the region, and path planning for each UAV from the same starting point (Figure 5).

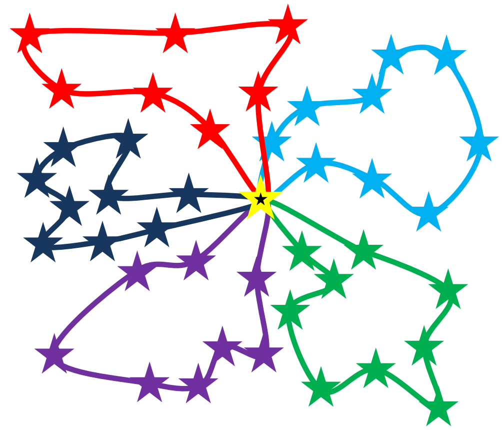


Figure 5. Multi-UAV path-planning from the same take-off location.

At this level, locations that require high attention, including near-fault structures, areas with landslides, infrastructures, and facilities related to health and safety, must be given higher priority. Therefore, a set of UAVs are assigned to each ROI, which can be formulated as a clustering problem, which is addressed by partitioning the ROI into multiple subregions. The number of UAVs available and their capabilities - maximum flight time, resolution, flight height, - are the main constraints to be considered. Well-established clustering techniques, such as spectral partitioning [32], *k*-means [33], and *k*-means++ [34], are employed in identifying a suitable range of subregions. In the following, the pseudocode of the *k*-means algorithm for this problem is presented:

Algorithm 1: *k*-means algorithm for optimal clustering of building footprints

Input: Building footprints, number of UAVs
Initialize: Randomly select the centroids equal to the number of UAVs (k)
While the centroid positions are not converged:

a) Calculate the distance of each building from the centroids
b) Assign each building to the nearest centroid
c) The buildings assigned to each centroid create a cluster
d) Move the position of centroids to the mean of the position of corresponding buildings

Output: The final clustering

When the clusters are defined, each UAV is assigned to its corresponding partitioned subregion, and an optimization problem is applied to discover the optimal flight path for each UAV. In this regard, a variation of the TSP is solved; however, TSP belongs to NP-hard problems, for which there is no quick and efficient solution algorithm [35, 36]. Metaheuristics are applied here to reach a reasonably good solution in a short time. For instance, GA, as an evolutionary metaheuristic, with a permutation operator is a proper choice to find optimal or near-optimal routes. The pseudocode of the GA for TSP is provided in the following:

Algorithm 2: TSP algorithm for multi-UAV path-planning

Input: Population size, the maximum number of generations, crossover rate, and mutation rate
Initialize: Generate initial tours randomly.

1. Evaluate the flight time of each tour using the traveled distance.
2. Sort the population based on fitness.
3. Select the best tours for the next generation.
4. **While** the number of iterations is less than the maximum number of generations:
   a) Create new tours by performing permutation crossover on the selected tours.
   b) Apply random mutation on the newly created tours.
   c) Evaluate the cost of the new tours.
   d) Combine the new tours with the original population and sort them based on fitness.
   e) Select the best tours to survive into the next generation.

Output: The best solution found during the search process

Level 3: NeRF-based 3D reconstruction

Over the past decade, novel methods have been introduced to perform 3D reconstruction using Structural-from-Motion (SfM). The main stages in 3D reconstruction using SfM are feature extraction, feature matching, geometric verification, and structure and motion reconstruction [37]. Recently, Neural Radiance Fields (NeRFs) were introduced by Mildenhall et al. [38] for synthesizing photo-realistic 3D reconstruction of complex scenes using 2D images. NeRFs are state-of-the-art data-driven approaches that learn to represent a 3D scene as a continuous function, and thus they are different from the traditional methods that require manual texture mapping and lighting. In contrast to the traditional 3D reconstruction methods, NeRFs do not rely on geometric primitives, such as triangles and voxels; instead, they train a neural network to directly model the scene's appearance. As a result, NeRFs have emerged as a promising method for generating highly accurate and realistic 3D digital scenes and have been successfully applied to a wide range of applications [6, 39]. At its core, a NeRF model represents a 3D scene as a radiance field that describes the color and volume density of the scene from every view angle [6], which can be written as:

$$F(\boldsymbol{x}, \theta, \phi) \rightarrow (\boldsymbol{c}, \sigma) \tag{5}$$

where $\boldsymbol{x}$ in the in-scene coordinate, θ is the azimuthal view angle, and ϕ is the polar view angle. $\boldsymbol{c}$ and σ are the color and density. A multi-layer perceptron (MLP), denoted as F_Θ in Figure 5, can approximate this 5D function.

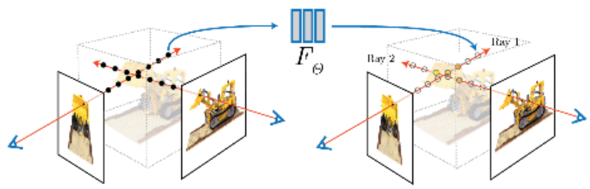


Figure 6. The NeRF volume rendering and training pipeline [38].

RESULTS AND DISCUSSIONS

The before-after satellite imagery, obtained from MAXAR [40, 41], was used for change detection to identify damaged buildings. The Bitemporal Image Transformer (BIT) model was employed to detect changes in building conditions before and after the 2023 Türkiye-Syria earthquake. The BIT model utilized a combination of transformers and CNNs to maximize the performance of the change detection task. The results in Figure 7 show that the model was effective in detecting changes in building conditions, and the damaged buildings were successfully identified.

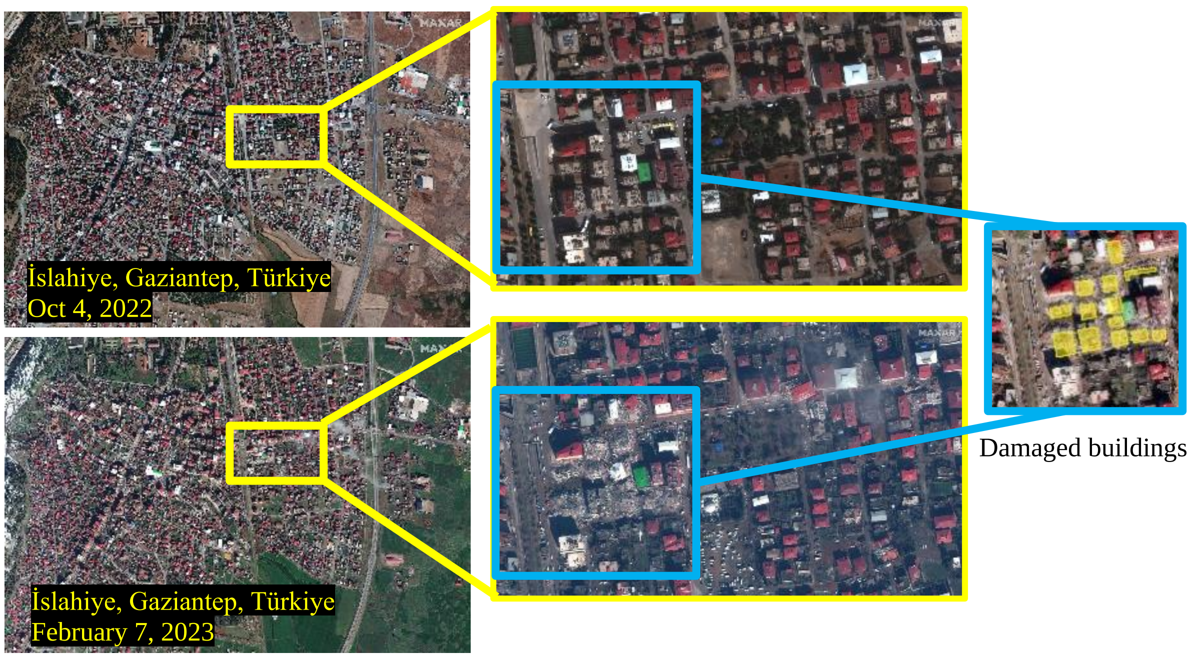


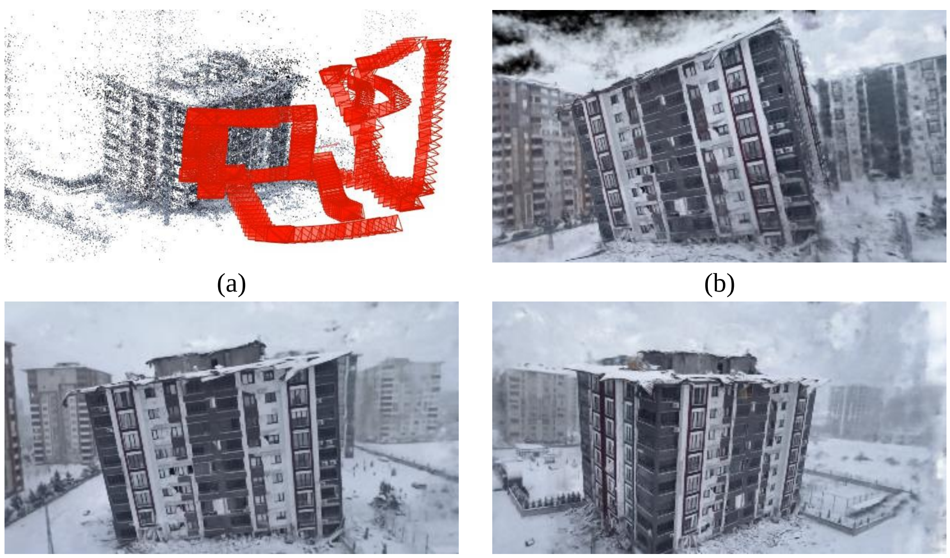
Figure 7. Regional damage assessment using change detection based on before-after satellite images.

The change detection approach using satellite imagery can provide valuable information for emergency responders and aid organizations to prioritize their efforts and allocate resources more efficiently. Based on the footprints obtained for the region of interest, the machine learning-based approach was utilized to find the optimal flight paths for UAV-based data collection. The three phases of the aerial imagery are shown in Figure 8, which include identifying the region of interest, clustering the building in the same neighborhood, and path planning for multiple UAVs. In this paper, The genetic algorithm was used for solving the traveling salesman problem, to minimize the length of the path. Specifically, we have considered the order of homes to be visited by the UAVs as decision variables and path length as the objective function. Each UAV is assigned to autonomously collect data from a subregion, for which the optimal path is found. As shown in this figure, the proposed approach could efficiently generate multiple routes for UAV-based inspection and data collection.

Region of interest | Clustering buildings | Multi-UAV path-planning

Figure 8. Optimal path-planning for multiple UAVs based on building footprints.

Türkiye has modern building codes, and many buildings in the southeastern province of Malatya's Bostanbaşı neighborhood (newly constructed luxury residences) did not collapse during the first earthquakes. However, many buildings suffered severe damage that led to the collapse during the second earthquake and the aftershocks. In this study, a NeRF-based algorithm was developed to reconstruct a 3D scene using a video captured by a UAV [42]. The 3D reconstruction using NeRF is shown in Figure 9, which highlights the capabilities of NeRF-based models in 3D scene reconstruction over the other traditional methods such as photogrammetry (Figure 9-(a)). The algorithm was able to capture the complex geometry of the scene with fine details while maintaining the texture of the buildings. The reconstructed scene also demonstrates accurate lighting and shading that results in photorealistic, coherent, and consistent results. It should be noted that NeRF-based models are also computationally expensive and require further research in optimizing the models for more efficient 3D reconstruction in real-world applications such as post-earthquake damage assessment and planning.



(a) (b) (c) (d)

Figure 9. Results of the 3D reconstruction: (a) SfM method (camera poses shown in red), (b)-(d) NeRF method.

CONCLUSIONS

This study aims to provide a multi-fidelity reconnaissance approach for a rapid post-disaster response. The methodology consists of three levels. Firstly, satellite images before and after the disaster are analyzed using state-of-the-art data-driven models to estimate regional damages. Secondly, the initial route of a UAV or a set of UAVs is determined automatically to obtain videos of damaged buildings within a neighborhood. Finally, the low-fidelity assessment results of the previous levels and information about the buildings are put together to mathematically model and optimize the flight route of UAVs to perform high-fidelity assessments such as 3D reconstructions. In Level 1, a Bitemporal Image Transformer (BIT) model is utilized for change detection using satellite imagery. In Level 2, a pipeline is proposed for optimal path planning, which includes identifying the region of interest, clustering the buildings in the region, and path planning for UAVs. Ultimately, in Level 3, Neural Radiance Field (NeRF)-based approach was proposed to obtain a photorealistic and accurate 3D reconstruction of specific buildings. The proposed multi-fidelity reconnaissance has demonstrated efficiency in achieving the desired outcome and has the potential to revolutionize post-disaster damage assessment and rapid response.

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