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Data-driven structural damage monitoring and assessment based on unmanned aerial vehicle images: a survey

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ABSTRACT

The increasing adoption of UAV-based remote sensing has transformed disaster response, structural health monitoring, urban building management, topographic change analysis, and disaster rescue. The collection of image information and the assessment of structural damage based on drones are key technologies for rapidly responding to disasters and providing strategic planning and deployment. Image-based assessment methods face challenges, including difficulty in extracting image features, multiple constraints on data acquisition, and difficulties in integrating evaluation results. This study provides a systematic review of UAV-based structural monitoring and assessment methodologies, categorizing existing techniques based on their data type and applications. This review clarifies the concepts and practical requirements of structural monitoring and assessment processes. Key technologies in data acquisition, map construction and model creation for regular monitoring and rescue assessment were sorted out. The selection of assessment models is closely related to the different types of maps. Finally, future developments in drone image evaluation are discussed and summarized, providing a reference for their application in civilian fields.

1. Introduction

Structural damage caused by natural disasters such as earthquakes, floods, and hurricanes results in substantial economic and human losses worldwide (Korhonen 2024; Reduction et al. 2023). Structural damage assessment is a key technology for achieving rapid response to disasters, which can reduce casualties and property damage. Conceptually, structural damage refers to adverse changes in the geometric or material characteristics of a system that is subjected to natural disasters such as floods, hurricanes, and earthquakes (Zhang et al. 2024a). In disaster scenarios, most of the damaged man-made structures are buildings. Urban buildings such as bridges, dams, and airport runways are the focus of attention in the civil fields. Natural changes in mountains, hills, and other wilderness environments are also considered. Traditional damage assessment methods require a significant investment by personnel and are time-consuming. The application of unmanned aerial vehicles (UAVs) has significantly improved the efficiency of information collection due to their low cost and high mobility. Therefore, the damage assessment of target structures based on UAV images has become a research hotspot and is of great significance for post-disaster rescue and strategic planning (Dai, Zhang, and Lin 2020; Wang et al. 2023b).

Most traditional structural damage assessment methods use remote sensing images captured by satellites. Remote sensing images have a large coverage area and stable operation, and can periodically obtain images of a certain area. However, satellites need to operate according to the corresponding orbit and cannot respond to sudden disasters. In addition, satellites cannot satisfy the requirements of detailed observation of models in key areas. With the development of UAV technology and the maturity of computer vision theory, drones equipped with visual sensors have the advantages of easy deployment and high mobility. High-resolution images captured by UAVs are increasingly being used in the field of damage assessment. Several reviews are based on deep learning methods and multi-source sensors (Cha et al. 2024; He et al. 2024; Zhang

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et al. 2024b). Unlike other reviews, the data type we focus on in this review is drone visual images. Damage assessment based on two-dimensional images is still flourishing, whereas damage assessment based on three-dimensional reconstruction is still in its infancy. Despite significant advancements in UAV-based monitoring, existing literature lacks a comprehensive synthesis of recent methodologies in structural health monitoring and damage assessment. Kerle et al. wrote a review focusing on drone imagery in 2020. We have reviewed the papers published in recent years. In addition, there are currently the following specific problems in the assessment of structural damage based on drone image information:

(1) **Various constraints during drone image acquisition and collection.** The battery life of a drone limits the effective time for data collection. The time required for a single drone to collect data is limited by multiple constraints. Therefore, the flight path and technical movements of the drone require more detailed planning. The application of multiple drones can improve the efficiency of data collection. Collaboration among UAVs requires more refined path planning, more precise positioning, and sensitive obstacle avoidance technology.

(2) **Limited application of constructed 3D models based on images.** These traditional 2D methods cannot reflect changes in the building height. Constructing 3D models based on images often requires a significant amount of computation and optimization time. Traditional feature extraction-based 3D reconstruction methods are unable to handle weakly textured environments. The insufficient application of 3D models can lead to an inability to accurately identify and evaluate small structural damages, such as cracks and deformations.

(3) **Visualization methods for daily monitoring need to be developed.** After collecting images using UAVs, the existing methods focus on different metrics for different types of target structures. Some methods express significant changes in newly constructed or demolished buildings, while others emphasize minor damages such as cracks. Damage assessment results are mainly based on manual experience and cannot provide quantitative results. It is difficult to guarantee scientificity and accuracy.

(4) **Insufficient robustness of traditional rescue assessment methods.** The analysis results of damage assessment are very important for subsequent rescue deployment therefore, there is a high demand for accurate and timely rescue assessment methods. In response to sudden natural disasters, wind, sand, rain, fog, smoke, and other conditions may affect the image quality of unmanned aerial vehicles, thereby affecting the damage assessment results. Under harsh and complex natural conditions, images collected by drones still exhibit blur, occlusion, and noise, and existing methods have low efficiency and limited robustness.

The remainder of this survey is organized as follows. Section 2 introduces the scope of this review and the architecture for damage assessment. Section 3 outlines the input types and related data processing methods. Section 4 summarizes the regular structural health monitoring methods. Section 5 provides a comprehensive analysis of the research and rescue assessment methods. Section 6 discusses the current development trends and opportunities. The conclusion is provided at the end of the survey.

2. Scope and architecture

In this section, we define the scope of this survey and the general architecture of this review.

2.1. Scope and dataset

Structural damage assessment and monitoring is a professional field that primarily focuses on conducting detailed inspections and analyses of critical man-made facilities such as buildings, bridges, tunnels and dams. This process involves a scientific assessment of the damage to these structures caused by sudden natural disasters such as earthquakes, floods, typhoons, prolonged natural erosion, material ageing, and wear and tear. Through this evaluation, the current state of the structure can be determined and its future safety and durability can be predicted, providing a basis for maintenance, repair, or reinforcement.

Drones carrying optical cameras have a wide range of applications in disaster rescue and daily monitoring scenarios. Therefore, damage assessment methods based on UAV images are discussed in this article.

Table 1. Datasets.

Name	Size	Comments	Citation
DDOS	34K	Thin structures Various applications Synthetic dataset	Kolbeinsson and Mikolajczyk (2024)
SynDrone	72K	Various applications Synthetic dataset	Rizzoli et al. (2023)
TartanAir	1M	Various applications Synthetic dataset	Wang et al. (2020)
Mid-Air	119K	Various applications Severe weather Synthetic dataset	Fonder and Droogenbroeck (2019)
NE-VBWD	15K	Real dataset Thin structures Sparse result	Stambler et al. (2019)
HazyDet	383K	Real dataset Severe weather Pseudo ground truth	Feng et al. (2024)
ABCD	8,506 pairs	Change Detection Detailed Annotations Real dataset	Fujita et al. (2017)
SECOND	4662 pairs	Semantic change detection Detailed Annotations Real dataset	Yang et al. (2020)
UAV-SD	10000 pairs	Change Detection Detailed Annotations Real dataset	Zhai et al. (2024)
LEVIR-SIM	637 pairs	Change Detection Detailed Annotations Real dataset	Chen and Shi (2020)
SMARS	9.0G	Various applications 2D/3D multimodal data Synthetic dataset	Fuentes Reyes et al. (2023)
RescueNet	4494	Segmentation Classification Real dataset	Rahnemoonfar, Chowdhury, and Murphy (2023)

We summarized several drone aerial photography datasets that support 3D reconstruction, change detection and other tasks. Their advantages and disadvantages are listed in Table 1. Obtaining ground truth for datasets collected from real environments is often difficult. However, synthetic datasets face a problem in that the acquired images may differ from those in the real environment.
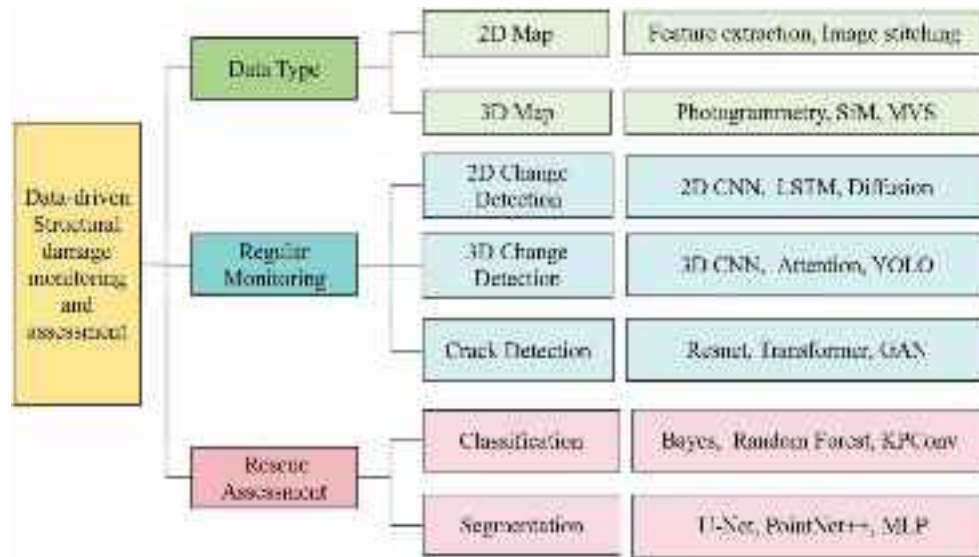
2.2. Architecture

The main framework of the damage assessment based on drone images can be summarized into three parts (data type, regular monitoring and rescue assessment), as shown in Figure 1. First, the UAV collects image information. These assessments can be classified according to the type of input data used. Two dimensional (2D) maps refer to large-scale two-dimensional models formed by stitching multiple images and include photos taken by drones in a single shot. Three-dimensional (3D) maps include three-dimensional models constructed using aerial photography and computer vision methods. Assessment methods based on 2D maps cannot reflect the changes in the height of a structure. Therefore, constructing 3D maps from UAV images is critical. The output types of 3D maps are point clouds, grids, volumes and digital elevation maps (DEM). A data-driven structural damage assessment is performed based on 2D maps or 3D maps. As shown in Figure 1, the structural monitoring and damage assessment methods based on drone images involve two key tasks: regular monitoring and rescue assessment. With the emergence of large data sets, more machine learning and deep learning methods have been utilized for damage assessment.

3. Data source and data type

3.1. Data source

The data source of the drone is related to the sensors it carries. Common sensors carried on drones include cameras, LiDAR, and infrared thermal imagers. Cameras are widely used because of their low cost. This

Figure 1. The architecture of data-driven structural damage monitoring and rescue assessment methods. The type of data and the target tasks influence the selection of the damage assessment methods.

study mainly focuses on drone image data. However, multi-modal data fusion can improve the accuracy of the damage assessment and structural health detection. Zhang et al. (2024b) analyzed the application of drones in the detection, inspection, and diagnosis of static and rotating wind turbine blades. He et al. (2024) summarized the status quo and challenges of UAV inspection in power systems with different sensors.

In most studies, researchers have adopted the manual operation mode of UAVs. Some researchers have used a beacon system to locate UAVs in areas with weak GPS, thus realizing the autonomous navigation system of UAVs. Kang and Cha (2018) utilize an ultrasonic beacon system to localize UAVs and use deep convolutional neural networks (CNN) to detect cracks. Ali et al. (2020) proposed an autonomous drone system based on Raspberry Pi and thermal infrared sensors, where both video and image data are obtained remotely from these sensors. Ali et al. (2021) combined ultrasonic beacon systems with computer vision damage segmentation and localization methods in real-time can improve the performance in avoiding obstacles and localizing UAVs. Waqas, Kang, and Cha (2024) integrated an improved convolutional neural network into an autonomous drone, achieving an average accuracy of 93.31%, and conducted experimental tests in a large parking structure.

Large-scale multi-modal data demands the drone's onboard computing, storage, and transmission capabilities. Relevant researchers propose using edge computing framework and edge artificial intelligence to alleviate this challenge. McEnroe, Wang, and Liyanage (2022) comprehensively summarize the contribution of edge AI to data transmission, autonomous navigation, flight control, and energy distribution on UAVs. With the development of hardware devices, Dong et al. (2021) propose to use UAVs as lightweight edge computing and caching servers for ground vehicles and computers.

3.2. Data type

Structural model assessment technologies can be divided into two-dimensional models (2D maps) and three-dimensional models (3D maps). The method of building a two-dimensional model involves pre-processing multiple images, and then splicing and fusing multiple images into a global two-dimensional map. 2D maps are easily accessible and can be processed in real-time. Evaluation methods based on 2D maps are still an active field. 3D maps can reflect the height information, but obtaining 3D maps requires specific devices or algorithms. Then this section discusses the 3D map reconstruction technology, which involves two disciplines: aerial photogrammetry and computer vision. Next, we summarize the basic

principles of the two disciplines used in 3D reconstruction (3D map construction) and discuss the advantages and disadvantages of these methods.

3.2.1. 2D maps

A drone remote-sensing image containing a target structure is a two-dimensional map (2D map). A global image stitched from multiple images is also a two-dimensional geometric map.

The 2D map construction technology includes image preprocessing, feature detection and matching, homography matrix calculation, image perspective transformation, and other steps. Image preprocessing includes general denoising, data compression, radiation correction, geometric correction, image enhancement and so on. Luo et al. (2023a) presented a shadow correction network to adjust the brightness and construct correction images. Gao et al. (2020) et al. proposed a new defoggy network.

The steps for stitching multiple two-dimensional images into a two-dimensional model also include image matching and image fusion. Image matching algorithms include grayscale-based matching and feature-based matching methods. Commonly used feature detection algorithms for drone image processing include SIFT (Lowe 2004), SURF (Bay et al. 2008), and ORB (Rublee et al. 2011). These algorithms effectively extract image features and use them for subsequent image stitching. Bu et al. (2016) completed the incremental stitching of multiple drone images using the SLAM algorithm and aligned the camera trajectory with the GPS trajectory. The mean errors in map accuracy are 3.066 and 5.710 m, respectively. Zhao et al. (2019) improved the SIFT algorithm to increase mosaicking efficiency. Their method reduces the time to stitch images to 2/3 of the original method. Zhang et al. (2021) also adopted the SIFT algorithm and calculated a homography matrix to generate a mosaicking map. Nath, Cheng, and Behzadan (2022) proposed a method for the spatial mapping of disaster impact information without relying on drone GPS data. Scale-invariant features were utilized in videos to perform step-by-step mapping of the disaster-stricken areas of two major North American hurricanes. Examples of 2D maps are shown in Figure 2.

3.2.2. 3D maps

The 3D reconstruction (3D map construction) process in computer vision includes sparse and dense reconstruction. Structure from motion (SfM) is a widely used technique for sparse reconstruction, recovering 3D structural information from multiple 2D images. SfM analyzes image sequence feature points to obtain sparse scene representations and camera positions by examining their mutual motion and geometric relationships. It matches features between images, calculates absolute camera pose in a unified coordinate system, and optimizes parameters via bundle adjustment (San, Jiang, and Jiang 2020). Related algorithms include the homography matrix calculation, the PnP algorithm, and triangulation. The above algorithms

(a)   (b)
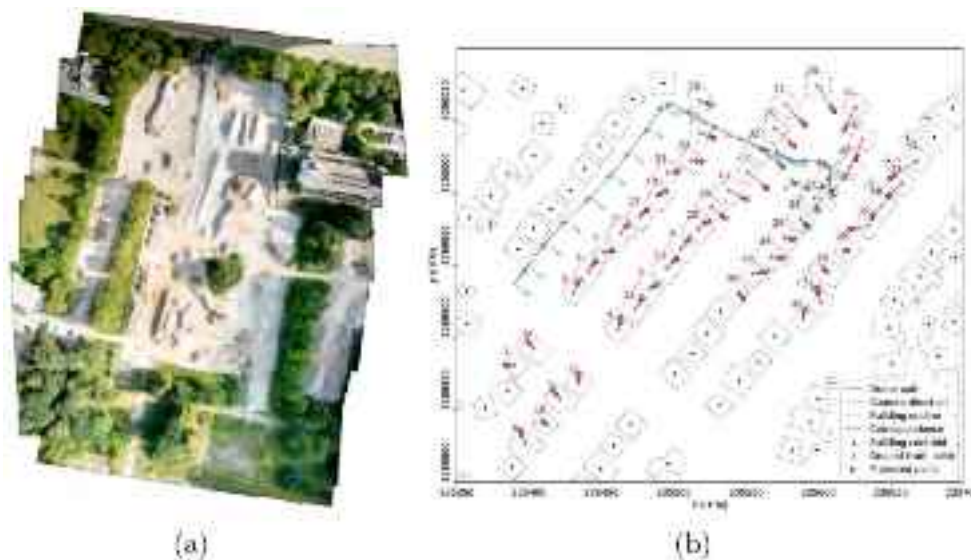
Figure 2. 2D map construction from UAV images. (a) is from Kekec, Yildirim, and Unel (2014) and (b) is from Nath, Cheng, and Behzadan (2022).

and steps are integrated into open-source software such as Visual SfM, Open MVG, Pix4D, DJI Terra, and PhotoScan. The functions of these software programs generally include parameter calculation, automatic aerial triangulation, matching editing, establishment of digital elevation models, and automatic drawing of contour lines. In addition, aerial photogrammetry and computer vision have the same theoretical basis. Aerial photogrammetry focuses on specific application needs and therefore has basic requirements for aerial photography (Cheng et al. 2024; Sayed Ishaq and Uğur 2021). Chen et al. (2019) and Mirzazade et al. (2021) both selected PhotoScan software to reconstruct 3D models. However, aerial photogrammetry is more advantageous in engineering and practicality.

Researchers have continuously developed SfM-based methods for 3D reconstruction. Wang et al. (2023a) used a bridge in an Italian road network as an example, compared the results generated by aerial photography with the measurement results of laser scanning, and verified the results of 3D reconstruction. Mandirola et al. (2022) used drones for bridge inspection and applied the SfM algorithm for point cloud reconstruction. Dippold and Tsai (2023) integrated multiple feature extractors into the SfM framework to improve the reconstruction performance. Luo et al. (2023b) used SfM and DJI drones to reconstruct the surface of the Yunnan volcanic craters at two different times and conducted a quantitative analysis. Arza-García et al. (2024) extracted the plane representing the gravel breakwater from the point cloud using the RANSAC algorithm and calculated the displacement caused by the storm. Liu et al. (2023) obtained real terrain models for different periods using the SfM method and displayed the distribution of surface deformation using the M3C2 metric. The average accuracy of the point cloud results in the X, Y, and Z directions are 44.80, 45.22, and 63.60 mm respectively. Zhao et al. (2021) obtained a high-precision 3D dam model generated using the SfM method for the emergency monitoring and inspection of dams. The authors conducted various types of damage assessment experiments on the dam model, with an error of 0.1-1.2 cm. Jiang et al. proposed a parallel SfM method for large-scale UAV map construction. Yao et al. developed a localization system based on visual odometry for a satellite denied environment. 3D maps are shown in Figure 3. As shown in Table 2, these methods based on SfM have accurate results. Mandirola et al. (2022) mentioned that the reconstructed time is 2.5 h. The SfM method has high accuracy through iterative optimization, but its real-time performance is limited.
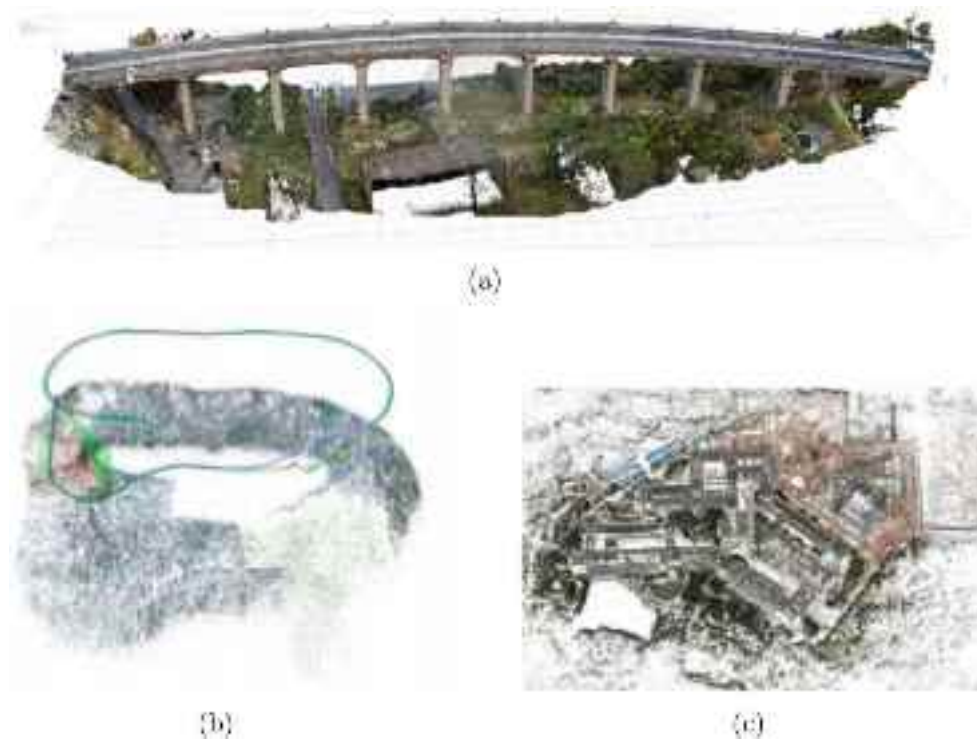
Figure 3. 3D map construction from UAV images. (a)-(c) are extracted from Wang et al. (2023a), Yao et al. (2024), Jiang et al. (2024).

Table 2. Accuracy of SfM-based methods.

No.	Comments	References
1	The mean Cloud 2 Cloud distance between the Laser Scanner and the UAV point cloud is 2.3 cm, 3.2 cm.	Wang et al. (2023a)
2	Residuals from ground control points are 3.8-17.8 mm.	Arza-García et al. (2024)
3	The average accuracy of the point cloud results in the X, Y, and Z directions are 44.80, 45.22, and 63.60 mm.	Liu et al. (2023)
4	The reconstructed dam model with an error of 0.1–1.2 cm.	Zhao et al. (2021)

Multi-view stereo methods (MVS) aim to reconstruct a dense 3D map from a set of images (Huang et al. 2024a). Stathopoulou et al. (2023) extended the classic PatchMatch method based on planar normals to solve the problem of incomplete reconstruction of artificial scenes. Hirschmuller (2008) presented the semi-global matching algorithm (SGM) and validated its effectiveness on an aerial image dataset. Khaloo et al. (2017) applied SURF features and a variant of SGM to generate a 3D model of a bridge.

In recent years, the application of deep learning methods in remote sensing has become a popular topic. Many researchers have attempted to utilize CNN and Transformer for the 3D reconstruction of UAV images (Godard, Aodha, and Brostow 2017). Cao et al. (2024) enhanced the feature extraction performance of binocular image pairs based on contrastive learning theory and the feature selection step. The CCStereo method obtained the smallest end-point error (1.511-4.715px) on the UAVStereo dataset. Mao et al. (2024) added a deformable sampling module to an end-to-end network to guide the complementary features between a reference image and other images. Subsequent monocular depth estimation methods based on CNN mostly relied on encoder and decoder structures (Knöbelreiter, Vogel, and Pock 2018; Madhuanand, Nex, and Yang 2021). Hermann et al. (2020) shared weights between the two networks to reduce the model size. Since 2021, there have been several studies on the three-dimensional reconstruction of drone images using differentiable renderers (Barron et al. 2021; Mildenhall et al. 2020; Turki, Ramanan, and Satyanarayanan 2022). Kim and Cha (2024) replaced the original image with the image segmentation result and then fed the image into the improved NeRF to obtain a 3D reconstruction result with damage mapping.

In summary, the 3D model reconstruction method based on multi-view geometry has high accuracy, but poor timeliness. These methods typically require considerable computational time. In addition, such methods rely on feature point extraction methods. therefore, they often cannot successfully reconstruct weak-texture scenes such as disasters. Methods based on deep learning have good real-time performance but poor generalization. These methods rely on the dataset size. With the expansion and enrichment of datasets, deep learning methods perform better in many scenarios.

4. Regular monitoring

Regular monitoring can be divided into two categories: obvious changes, such as new construction and demolition, and potential changes, such as cracks that may affect safety. This section summarizes related work on 2D change detection, 3D change detection and crack detection.
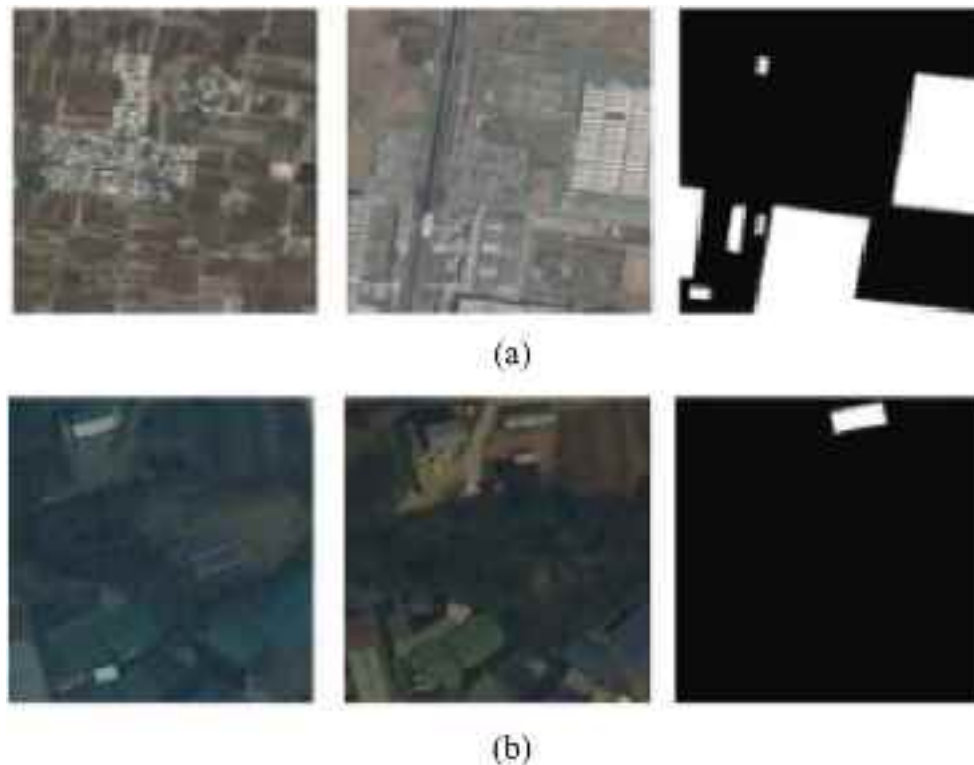
4.1. 2D change detection

Various change detection were employed on the basis of 2D maps. Sun et al. (2022) used convolution and long short-term memory (LSTM) as the primary frameworks for change detection in a network. The accuracy of the proposed method on SZTAKI and BeiChuan datasets reaches 90.10% and 88.37%, respectively. Feng et al. (2023) utilized self-supervised learning to reduce the need for labeled data in remote sensing images and proposed innovative spatial analysis rules to improve the accuracy and efficiency of 2D building change detection. Chen et al. (2024a) presented a supervised network based on the Transformer backbone to enhance the correlation between damaged buildings. Wang et al. (2024) used semantic information as prior knowledge and employed 3D convolution and contrastive learning methods to enhance the accuracy of change detection methods. This method has an accuracy of 90.07% and an F1 metric of 63.70% on the aerial images dataset. Lin, Yang, and Zhang (2023) used pseudo-transitional videos and temporal encoders to prevent information loss, and solved the difficulty of extracting spatiotemporal features from remote sensing images utilizing video understanding techniques. Fang et al. (2024) enhanced the ability of a network to aggregate high resolution features based on a Siamese structure. This method achieves 73.27% and 87.55%

in mIoU and accuracy, respectively. Yang, Yuan, and Li (2024) extracted spatial features using a CNN architecture and decomposed the features into high frequency and low-frequency information using wavelet transform to obtain more ideal segmentation results. Zhai et al. (2024) placed an attention module in a feature fusion network and used a classifier to determine the differences between UAV images. Wen et al. (2024) combined Transformer and diffusion models to generate predicted change positions based on local spatial information. Fang et al. (2023) utilized four different aggregation networks to fuse information at different levels and comprehensively considered multiple probability results to optimize segmentation results. Zheng et al. (2024) presented an unsupervised adaptation network to quickly complete building damage assessments. The results are shown in Figure 4.

4.2. 3D change detection

The changes in the 3D reconstruction results obtained at different times reflect the damage to the structure. Gomroki, Hasanlou, and Chanussot (2023) solved the problem of data imbalance by stitching two images together as a data augmentation method. They used Yolov7 as a backbone network and improved it to build the categories involved in 3D change detection. The proposed method obtains an average accuracy of 94.87% on Mashhad UAV dataset. Ngeljaratan, Bas, and Moustafa (2024) demonstrated that 3D reconstruction based on drone images can be used to monitor the natural gas pipeline infrastructure. Zhao et al. (2021) constructed 3D models through SfM and used the distance metric between points for damage detection. The authors performed quantitative experiments on a scaled-down dam model and statistically found that the error between the true and predicted values ranged from −0.3 to 1.2 cm. Liu et al. (2024a) used a Transformer as a backbone network to extract features from digital surface models and 2D images and then utilized a cross-modal fusion module for feature aggregation. They established the consistency constraints for semantic segmentation and height variation by using a loss function. Experiments illustrated that the Transformer-based method can obtain the smallest RMSE (1.273) on the height change detection task. Fuentes Reyes et al. (2023) proposed a synthetic dataset called SMARS for urban semantic segmentation, change detection, and building extraction tasks. Huang et al. (2024b) designed a large-scale long-term


(a)

(b)

Figure 4. Damage assessment based on 2D change detetction. (a) and (b) are extracted from Zhang and Liu (2024), Feng et al. (2023).

urban street view dataset, which was used to detect physical changes in buildings. De Gélis, Lefèvre, and Corpetti (2023) proposed an unsupervised cluster network for 3D change detection. The 3D change detection results are shown in Figure 5.

4.3. Crack detection

Crack identification is an important task in structural health monitoring. Liu et al. (2024b) first analyzed the reasons for the reduced effectiveness of crack recognition in concrete and pavement and proposed a deblurring network that combines motion information and accumulated events. Xiang et al. (2023) designed a lightweight module based on the Yolov5 framework to reduce the model's parameters and introduced an improved intersection over the union loss function to enhance the model's generalization to irregular targets. The comparative experiment showed the accuracy of GC-Yolov5 is 0.769. Xing, Liu, and Zhang (2023) replaced the feature extraction backbone network in the YoloV5 model with Swin Transformer and conducted network performance tests on a road crack dataset created by themselves for complex backgrounds. Zhao et al. (2023) proposed a network for extracting cracks and a network for classifying cracks, and applied both two networks to road surfaces over 100 kilometers for experimental verification. Munawar et al. (2022) proposed a building crack detection method based on deep learning using a 16-layer CNN architecture that can automatically learn and extract crack features in images without the need for manual feature extraction. The CycleGAN deep learning model was introduced to convert crack images into real images, thereby generating more reliable and realistic images without the need for paired data training. CycleGAN can automatically train models without manually labeling a large amount of data, thereby reducing the cost and difficulty of data collection and annotation. This method achieved the class average accuracy of 0.939 on the test dataset. Miao et al. (2021) studied the use of pixel-level multi-class detection technology to identify
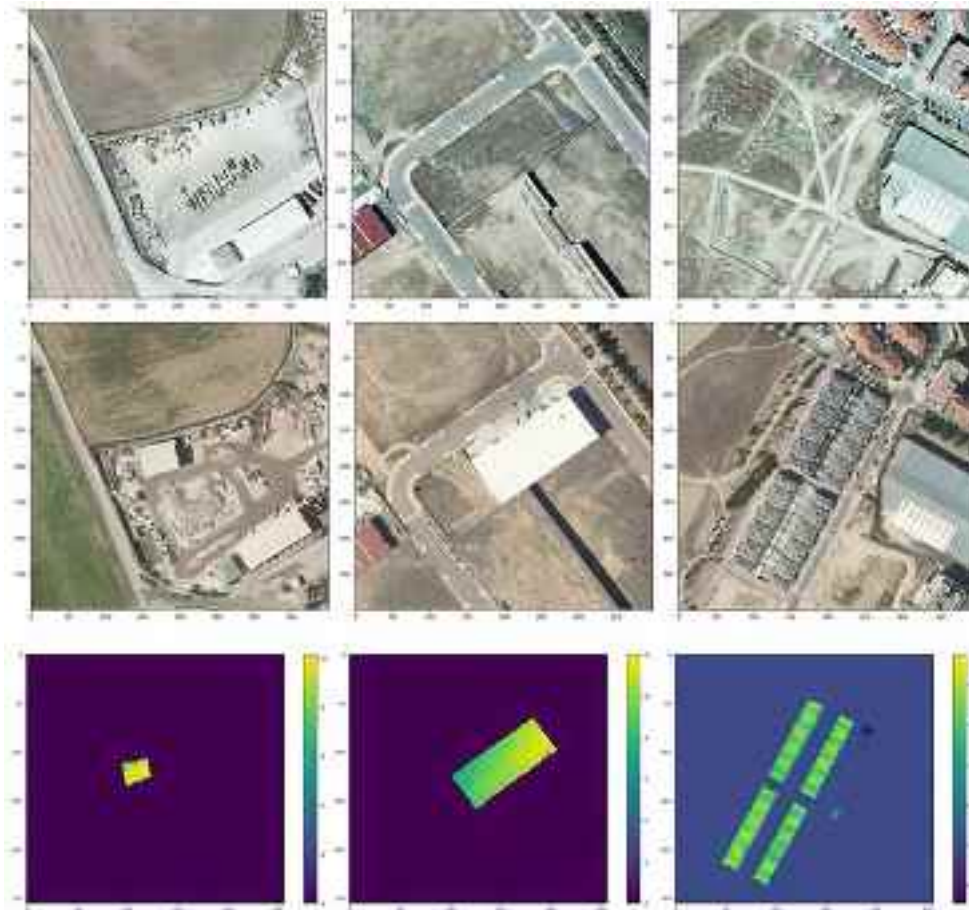
Figure 5. Damage assessment based on 3d change detection methods (Marsocci et al. 2023).

visible damage (such as cracks, concrete spalling and crushing, exposed steel bars, buckling, and fractures) in reinforced concrete components. This study constructed an image database with pixel level multi-class annotations specifically for the damage detection task of reinforced concrete components.

Cha, Choi, and Büyüköztürk (2017) experimentally demonstrated that the convolutional neural network-based method performs better than traditional edge detection methods in conditions such as lighting and shadow. Cha et al. (2018) constructed a damage dataset containing five types of damage and 2,366 images. They trained a structural visual inspection method based on a convolutional neural network on this dataset, with an average accuracy of 84.7%. Choi and Cha (2019) proposed a new semantic damage detection model based on convolutional neural networks and trained it on a self-built crack dataset to obtain a smaller model and real-time processing speed. Kang and Cha (2022) proposed a crack segmentation network based on the multi-head attention mechanism, which achieved scores above 90% for indicators such as precision, recall, F1 score and mIoU, and the processing speed of the model reached 49.2 frames per second.

In conclusion, change detection is a hot topic and crack detection is widely used. Daily monitoring is important for civil facilities. The inputs to change detection algorithms are categorized into 2D images and 3D models, which leads to different network structures. Data-driven methods have high requirements for datasets. The construction of change detection datasets requires continuous collection over a long period, with some comparative data spanning several years. Crack detection datasets require images containing many different types of cracks.

5. Rescue assessment

Accurate and complete 3D representations of architectural structures are crucial for structural health assessments Koszyk et al. (2024). After obtaining a three-dimensional model, researchers from different disciplines simulated or inferred the degree of damage using basic laws. Researchers with a foundation in mechanics are accustomed to using numerical methods and verification tests to analyze the laws of damage, such as establishing damage trees (Dang 2021; Melo et al. 2020) and conducting numerical simulation tests. However, some researchers used data features to identify and predict damage results, such as the use of convolutional neural networks to identify cracks. Researchers have classified this problem as a classification, recognition, or segmentation problem that requires the collection and construction of datasets according to the objectives. The following will be summarized in the sections below.

5.1. Segmentation

The combination of 3D reconstruction and semantic segmentation methods is a popular research topic. The classification of building damage levels and the segmentation of damaged components are crucial for rescue decision-making.

Forcael et al. (2024) studied a method for evaluating cracks in bridges using a digital image-capturing technology performed by drones. By analyzing the images captured by drones, researchers have been able to accurately identify and assess the damage to bridge structures, thereby providing effective technical support for bridge maintenance and management. Han et al. (2024) constructed a new large-scale real city 3D dataset with rich categories and pixel-by-pixel semantic instance segmentation annotations. They used U-Net and feature aggregation modules for feature extraction and fed the aggregated features into instance prediction and semantic prediction modules, respectively. Koszyk et al. (2024) utilized the PointNet++ network to perform semantic segmentation of ground and non-ground objects. Kharroubi et al. (2024) provided a dataset for 3D semantic segmentation of artificial buildings near railways and validated the performance of advanced models through experiments. Wang et al. (2023) proposed a post-earthquake building structural component segmentation method based on the deep fusion learning of geometric information, as shown in Figure 6. This study constructs an enhanced U-Net model and introduces a new synthetic loss function containing a geometric consistency (GC) term.

Kumar Jagatheesaperumal et al. (2024) emphasized the contribution of visual serving technology to improving the precision and accuracy of UAVs in disaster scenarios, and combined with the latest advances in deep learning, analyzed the application of this integrated technology in search and rescue, damage
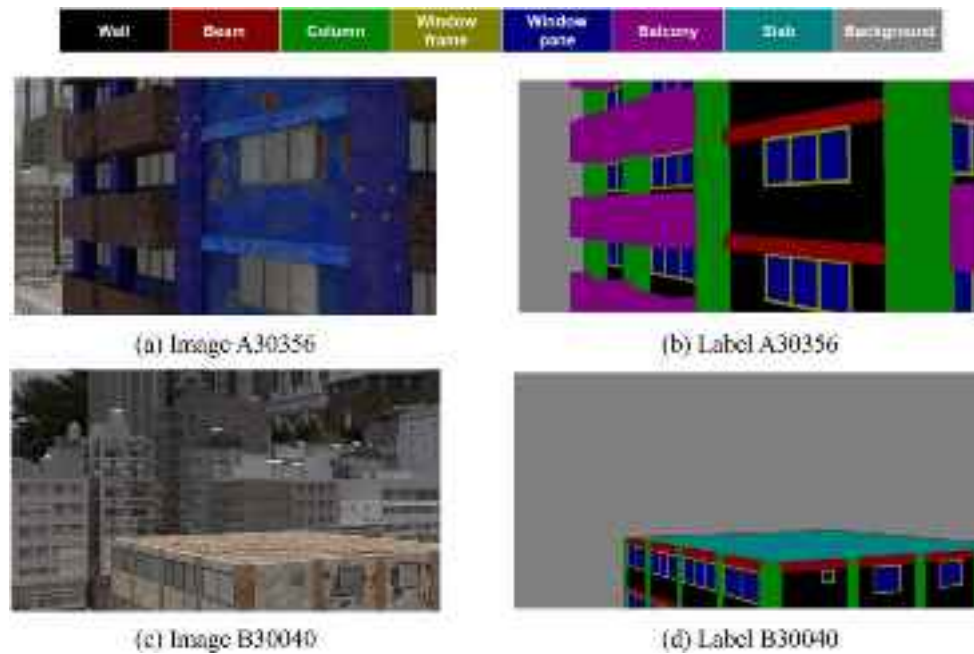
Figure 6. Damage assessment based on segmentation methods (Wang et al. 2023).

assessment, and situation awareness. Gwon et al. (2023) proposed a structural damage data enhancement method based on image-to-image conversion for the application of UAVs in infrastructure inspection. This method uses images collected by UAVs and image conversion technology to enhance the structural damage data, thereby improving the accuracy and robustness of the detection model.

5.2. Classification

Methods for structural damage assessment play an important role in disaster relief (Fujita et al. 2017). Cheng, Behzadan, and Noshadravan (2021) proposed a building localization model based on Mask R-CNN and trained the MobileNet on the interior visual dataset of hurricane dorian with the earth mover distance (EMD^2) loss. The trained model achieved 65.6% in building location accuracy and 61% in classification accuracy. Finally, the damage assessment results were compared with those in existing literature by studying the relationships between building size, number of floors, and disaster damage severity. Hong et al. (2022b) introduced a new convolutional neural network based on post-disaster aerial images, namely the earthquake building damage classification network (EBDC-Net), which was used to assess the extent of building damage. In the experiment, the overall classification accuracies were 94.44%, 85.53%, and 77.49% when the building damage was divided into two, three, and four categories, respectively. Jozi et al. (2024) utilized a naive Bayes classifier and extracted texture and edge features to classify the damaged and undamaged conditions of post-disaster houses, as shown in Figure 7. This method can achieve an accuracy of 89.3% on real post-disaster images. Shirzad-Ghaleroudkhani et al. (2024) used images captured by drones after disasters as inputs and applied a naive Bayes classification method to assess the severity of building damage.

Li and Tang (2018) determined the level of building damage based on the characteristics of the point clouds and spectral images. Drones play an important role in the search and rescue field because of their mobility and flexibility (Lyu et al. 2023). Rahnemoonfar, Chowdhury, and Murphy (2023) created an image dataset of disaster-stricken areas collected using UAVs after a hurricane. This dataset provides the ground truth for multiple class segmentation tasks and pixel-level annotations for the damage levels of each class. Zahs et al. (2023) categorized building damage after earthquakes into three levels based on their severity. First, the authors used clustering algorithms to extract the changing parts of a building and then utilized a random forest classifier to classify the point cloud. The point cloud-based damage assessment method achieved an accuracy of 92%–95% on real datasets. Hong et al. (2022a) applied

Figure 7. Damage assessment based on classification methods (Jozi et al. 2024).

CasMVSNet to aerial images captured in the Yunnan Province and evaluated building damage based on reconstructed point clouds. The authors experimentally demonstrate that point cloud-based damage assessment methods can also meet the needs of rescue in terms of timeliness. He et al. (2023) used a grey-level co-occurrence matrix for feature extraction and conducted a damage assessment based on a cloud model. The Transformer network outperforms the traditional CNN in assessing the severity of damage based on a quantitative building assessment (Asad et al. 2023). CNN is effective in extracting local features in images, while Transformer focuses on the global context. Zhang and Liu (2024) utilized similarity and boundary constraints to enhance the attention of a network to changing regions, thereby improving its generalization to class-imbalance problems.

In summary, the advantage of a damage assessment method based on data features is that it is relatively intuitive. Utilizing deep learning methods, tiny damage details can be automatically identified, thereby improving the accuracy and timeliness of the assessment. However, the methods based on data rules also have problems. Data-driven methods rely heavily on image quality and shooting environment. For example, occlusion in an image, noise caused by a drone moving too quickly, and smoke in a dynamic environment may cause assessment errors. In addition, the classification, recognition, and segmentation methods based on deep learning are highly dependent on large-scale datasets. However, there are certain difficulties in constructing damaged data sets in actual operation. In the civilian field, although drones can capture closeup photographs of damaged buildings or equipment after a disaster, labeling a large number of images of damaged parts is challenging.

6. Development trend

With the continuous development of UAV equipment hardware and the gradual maturity of deep learning technology, new trends are emerging in the research of UAV-based image acquisition and structural damage assessment. This paper sorts out several possible development directions based on the actual needs of the assessment system and the limitations of existing technologies.

Image perception in complex scenes: Most existing work requires that image acquisition be performed under conditions where there is sufficient lighting to capture clear target structures. Post-disaster scenes may present a variety of different conditions, which pose a series of challenges to image processing, such as heavy fog, blowing sand, and smoke. In such complex scenes, the accuracy and robustness of image perception become critical. In addition, in rescue scenes, target structures may be camouflaged or blocked, which requires future image processing technology to have stronger adaptability and recognition capabilities and effectively deal with interference factors in complex environments.

The balance between speed and accuracy in 3D reconstruction: UAVs can quickly enter disaster-stricken areas to obtain first-hand information after a disaster due to their high flexibility. The ability to process real-time data based on images should be improved to provide feedback on structural damage

information for a timely response. Data integration and real-time analysis platforms are required to manage and analyze the data collected by UAVs and provide intuitive damage assessment reports. The 3D reconstruction method using 2D images typically requires a significant amount of post-processing time. Therefore, the 3D reconstruction method must find a balance between speed and accuracy.

Digital twin models combining physical attributes: The damage assessment method needs to adapt to complex scenarios and show high adaptability to ensure structural damage can be accurately assessed in various environments. However, the current methods often only evaluate and classify images after a certain type of disaster. The collection of such data often requires a long period of accumulation. A digital twin is one of the solutions. Researchers can enhance the accuracy and generalization of evaluation models by assigning physical properties to existing 3D reconstructed models and simulating loss images caused by different types and degrees of natural disasters through existing patterns.

Virtual reality (VR) application for full cycle management and staff training: Structural health monitoring is a long-term and regular task that requires monitoring personnel to conduct multiple drone flights at different times. Importing 3D reconstruction models into virtual reality (VR) environments and regularly updating them can achieve the full lifecycle monitoring of important facilities. In addition, the constructed VR environment can be used to train personnel. Based on the virtual 3D models, drone operators can detect damaged areas in advance and design flight routes in advance. In the virtual reality environment, the designed flight routes and movements can be evaluated to improve work efficiency and reduce training time.

Multi-modal data fusion based on edge artificial intelligence: Deep learning models based on multi-modal data are developing rapidly. With the development of hardware, drones could carry more types of sensors. Multi-modal data fusion methods based on edge artificial intelligence algorithms can further improve the perception ability and decision-making efficiency of drones in complex environments. The multimodal data collected on the UAV may contain 2D images, 3D point cloud data, position data, etc. Therefore, multi-modal data fusion techniques include fusion techniques between different types of 2D images, registration techniques for 2D images and 3D point clouds, temporal alignment of position data with image data, etc.

7. Conclusion

Structural health monitoring and damage assessment based on drone images play a vital role in the civil field. This paper provides a comprehensive review of relevant methods based on drone visual imagery for regular monitoring and disaster rescue assessment. Commonly used public datasets and the performance of state-of-the-art methods are summarized. However, there are still many problems in damage effect assessment technology, including the balance between real-time and accuracy of the detection algorithm, the standardization and adaptability of the assessment method, and the impact of dynamic and complex environments. These problems need to be solved through the process of data acquisition, geometric maps and assessment model construction. Future developmental trends are also described. The state-of-the-art technologies summarized in this study hold significant value for researchers, engineers and rescue decision-makers. Researchers and engineers gain insights into AI and UAV remote sensing and develop rescue systems. Response teams obtain tools for faster, more accurate decision-making, which bridging innovation with practical disaster mitigation.

Author contributions

Zhuoyue Yang: Conceptualization, Methodology, data curation, investigation, writing-original draft preparation, writing-review & editing, visualization. Yuxin Xu: Conceptualization, project administration, supervision, writing-review & editing. Hao Song: Data curation, investigation. Kang Yu: Data curation, investigation

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Data availability statement

This is a review paper, no data has been used, and open data has been presented and referenced in the article.

References

Ali, R., D. Kang, G. Suh, and Y. Cha. 2021. "Real-Time Multiple Damage Mapping Using Autonomous UAV and Deep Faster Region-Based Neural Networks for GPS-Denied Structures." *Automation in Construction* 130:103831. https://doi.org/10.1016/j.autcon.2021.103831.

Ali, R., J. Zeng, M. Kavgic, and Y. Cha. 2020. "Heat Loss Detection Using Thermal Imaging by a Small UAV Prototype." Proc. SPIE 11382, Smart Structures and NDE for Industry 4.0, Smart Cities, and Energy Systems, 113820S. https://doi.org/10.1117/12.2557902.

Arza-García, M., J. Goncalves, V. Ferreira Pinto, and G. Bastos. 2024. "On-Site Stability Assessment of Rubble Mound Breakwaters Using Unmanned Aerial Vehicle-Based Photogrammetry and Random Sample Consensus." *Remote Sensing* 16 (2): 331. https://doi.org/10.3390/rs16020331.

Asad, M., M. Asim, M. Awan, and M. Yousaf. 2023. "Natural Disaster Damage Assessment Using Semantic Segmentation of UAV Imagery." 2023 international Conference on Robotics and Automation in Industry, 1–7. https://doi.org/10.1109/ICRAI57502.2023.10089539.

Barron, T., B. Mildenhall, M. Tancik, P. Hedman, R. Brualla, and P. Srinivasan. 2021. "Mip-NeRF: A Multiscale Representation for Anti- Aliasing Neural Radiance Fields." 2021 IEEE/CVF International Conference on Computer Vision, 5835–5844. https://doi.org/10.1109/ICCV48922.2021.00580.

Bay, H., A. Ess, T. Tuytelaars, and L. Gool. 2008. "Speeded-Up Robust Features (SURF)." *Computer Vision and Image Understanding* 110 (3): 346–359. https://doi.org/10.1016/j.cviu.2007.09.014.

Bu, S., Y. Zhao, G. Wan, and Z. Liu. 2016. "Map2DFusion: Real- Time Incremental UAV Image Mosaicing Based on Monocular SLAM." 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems, 4564–4571. https://doi.org/10.1109/IROS.2016.7759672.

Cao, X., X. Zhang, A. Yu, W. Yu, and S. Bu. 2024. "CSStereo: A UAV Scenarios Stereo Matching Network Enhanced with Contrastive Learning and Feature Selection." *International Journal of Applied Earth Observation and Geoinformation* 134:104189. https://doi.org/10.1016/j.jag.2024.104189.

Cha, Y., R. Ali, J. Lewis, and O. Büyüköztürk. 2024. "Deep Learning-Based Structural Health Monitoring." *Automation in Construction* 161:105328. https://doi.org/10.1016/j.autcon.2024.105328.

Cha, Y., W. Choi, and O. Büyüköztürk. 2017. "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks." *Computer-Aided Civil and Infrastructure Engineering* 32 (5): 361–378. https://doi.org/10.1111/mice.12263.

Cha, Y., W. Choi, G. Suh, S. Mahmoudkhani, and O. Büyüköztürk. 2018. "Autonomous Structural Visual Inspection Using Region-Based Deep Learning for Detecting Multiple Damage Types." *Computer-Aided Civil and Infrastructure Engineering* 33 (9): 731–747. https://doi.org/10.1111/mice.12334.

Chen, S., Debra F. Laefer, E. Mangina, I. Zolanvari, and J. Byrne. 2019. "UAV Bridge Inspection through Evaluated 3D Reconstructions." *Journal of Bridge Engineering* 24 (4): 05019001. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001343.

Chen, F., S. Yao, L. Wang, N. Wang, H. Zhao, and Y. Bo. 2024a. "HRTBDA: A Network for Post-disaster Building Damage Assessment Based on Remote Sensing Images." *International Journal of Digital Earth* 17 (1): 2418880. https://doi.org/10.1080/17538947.2024.2418880.

Cheng, C., Amir H. Behzadan, and Arash Noshadravan. 2021. "Deep Learning for Post- Hurricane Aerial Damage Assessment of Buildings." *Computer-Aided Civil and Infrastructure Engineering* 36 (6): 695–710. https://doi.org/10.1111/mice.12658.

Cheng, C., L. Luo, S. Murphy, Y. Lee, and F. Leite. 2024. "A Framework to Enhance Disaster Debris Estimation with AI and Aerial Photogrammetry." *International Journal of Disaster Risk Reduction* 107:104468. https://doi.org/10.1016/j.ijdrr.2024.104468.

Choi, W., and Y. Cha. 2019. "SDDNet: Real-Time Crack Segmentation." *IEEE Transactions on Industrial Electronics* 67 (9): 8016–8025. https://doi.org/10.1109/TIE.2019.2945265.

Dai, C., Z. Zhang, and D. Lin. 2020. "An Object-Based Bidirectional Method for Integrated Building Extraction and Change Detection Between Multimodal Point Clouds." *Remote Sensing* 12 (10): 1680. https://doi.org/10.3390/rs12101680.

Dang, Xiaobin. 2021. "Application of 3D Laser Scanning Technology in Monitoring Deformation of Port Trail." *IOP Conference Series: Earth and Environmental Science* 783 (1): 012151. https://doi.org/10.1088/1755-1315/783/1/012151.

De Gélis, I., S. Lefèvre, and T. Corpetti. 2023. "DC3DCD: Unsupervised Learning for Multiclass 3D Point Cloud Change Detection." *ISPRS Journal of Photogrammetry and Remote Sensing* 206:168–183. https://doi.org/10.1016/j.isprsjprs.2023.10.022.

Dippold, E., and F. Tsai. 2023. "Two-View Structure-from-Motion with Multiple Feature Detector Operators." *Remote Sensing* 15 (3): 605. https://doi.org/10.3390/rs15030605.

Dong, C., Y. Shen, Y. Qu, K. Wang, J. Zheng, Q. Wu, and F. Wu. 2021. "UAVs as an Intelligent Service: Boosting Edge Intelligence for Air-Ground Integrated Networks." *IEEE Network* 35 (4): 167–175. https://doi.org/10.1109/MNET.011.2000651.

Fang, H., S. Guo, P. Zhang, W. Zhang, X. Wang, S. Liu, and P. Du. 2023. "Scene Change Detection by Differential Aggregation Network and Class Probability- Based Fusion Strategy." *IEEE Transactions on Geoscience and Remote Sensing* 61:1–18. https://doi.org/10.1109/TGRS.2023.3317701.

Fang, S., W. Li, S. Yang, Z. Li, J. Zhao, and X. Wang. 2024. "BT-HRSCD: High-Resolution Feature Is What You Need for a Semantic Change Detection Network With a Triple-Decoding Branch." *IEEE Transactions on Geoscience and Remote Sensing* 62:1–14. https://doi.org/10.1109/TGRS.2024.3500790.

Feng, W., F. Guan, J. Tu, C. Sun, and W. Xu. 2023. "Detection of Changes in Buildings in Remote Sensing Images via Self-Supervised Contrastive Pre-Training and Historical Geographic Information System Vector Maps." *Remote Sensing* 15 (24): 5670. https://doi.org/10.3390/rs15245670.

Feng, C., Z. Chen, X. Li, C. Wang, J. Yang, M. Cheng, Y. Dai, and Q. Fu. 2024. "HazyDet: Open-source Benchmark for Drone-view Object Detection with Depth-cues in Hazy Scenes." *arXiv preprint arXiv:2409.19833*.

Fonder M., and M. V. Droogenbroeck. 2019. "Mid-air: A Multi-modal Dataset for Extremely Low Altitude Drone Flights." *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 553–562. https://doi.org/10.1109/CVPRW.2019.00081.

Forcael, E., O. Román, H. Stuardo, R. Herrera, and J. Soto- Mũnoz. 2024. "Evaluation of Fissures and Cracks in Bridges by Applying Digital Image Capture Techniques Using an Unmanned Aerial Vehicle." *Drones* 8 (1): 8. https://doi.org/10.3390/drones8010008.

Fuentes Reyes, M., Y. Xie, X. Yuan, P. d'Angelo, F. Kurz, D. Cerra, and J. Tian. 2023. "A 2D/3D Multimodal Data Simulation Approach with Applications on Urban Semantic Segmentation, Building Extraction and Change Detection." *ISPRS Journal of Photogrammetry and Remote Sensing* 205:74–97. https://doi.org/10.1016/j.isprsjprs.2023.09.013.

Fujita, Aito, Ken Sakurada, Tomoyuki Imaizumi, Riho Ito, Shuhei Hikosaka, and Ryosuke Nakamura. 2017. *Damage Detection from Aerial Images via Convolutional Neural Networks*, 5–8. https://doi.org/10.23919/MVA.2017.7986759.

Gao, T., K. Li, T. Chen, M. Liu, S. Mei, K. Xing, and Y. Li. 2020. "A Novel UAV Sensing Image Defogging Method." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13:2610–2625. https://doi.org/10.1109/JSTARS.2020.2998517.

Godard, C., O. Aodha, and G. Brostow. 2017. "Unsupervised Monocular Depth Estimation with Left-Right Consistency." 2017 IEEE Conference on Computer Vision and Pattern Recognition, 6602–6611. https://doi.org/10.1109/CVPR.2017.699.

Gomroki, M., M. Hasanlou, and J. Chanussot. 2023. "Automatic 3D Multiple Building Change Detection Model Based on Encoder–Decoder Network Using Highly Unbalanced Remote Sensing Datasets." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 16:10311–10325. https://doi.org/10.1109/JSTARS.2023.3328561.

Gwon, G., J. Lee, I. Kim, S. Baek, and H. Jung. 2023. "Image-to-Image Translation-Based Structural Damage Data Augmentation for Infrastructure Inspection Using Unmanned Aerial Vehicle." *Drones* 7 (11): 666. https://doi.org/10.3390/drones7110666.

Han, X., C. Liu, Y. Zhou, K. Tan, Z. Dong, and B. Yang. 2024. "WHU-Urban3D: An Urban Scene LiDAR Point Cloud Dataset for Semantic Instance Segmentation." *ISPRS Journal of Photogrammetry and Remote Sensing* 209:500–513. https://doi.org/10.1016/j.isprsjprs.2024.02.007.

He, Y., Z. Liu, Y. Guo, Q. Zhu, Y. Fang, Y. Yin, Y. Wang, B. Zhang, and Z. Liu. 2024. "UAV Based Sensing and Imaging Technologies for Power System Detection, Monitoring and Inspection: A Review." *Nondestructive Testing and Evaluation*: 1–68. https://doi.org/10.1080/10589759.2024.2421938.

He, J., L. Shao, Y. Li, K. Wang, and W. Liu. 2023. "Pavement Damage Identification and Evaluation in UAV-Captured Images Using Gray Level Co-Occurrence Matrix and Cloud Model." *Journal of King Saud University - Computer and Information Sciences* 35 (9): 101762. https://doi.org/10.1016/j.jksuci.2023.101762.

Hermann, M., B. Ruf, M. Weinmann, and S. Hinz. 2020. "Self-supervised Learning for Monocular Depth Estimation from Aerial Imagery." *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* V-2-2020:357–364. https://doi.org/10.5194/isprs-annals-V-2-2020-357-2020.

Hirschmuller, H. 2008. "Stereo Processing by Semiglobal Matching and Mutual Information." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 30 (2): 328–341. https://doi.org/10.1109/TPAMI.2007.1166.

Hong, Z., Y. Yang, J. Liu, S. Jiang, H. Pan, R. Zhou, Y. Zhang, et al. 2022a. "Enhancing 3D Reconstruction Model by Deep Learning and Its Application in Building Damage Assessment After Earthquake." *Applied Sciences* 12 (19): 9790. https://doi.org/10.3390/app12199790.

Hong, Z., H. Zhong, H. Pan, J. Liu, R. Zhou, Y. Zhang, Y. Han, J. Wang, S. Yang, and C. Zhong. 2022b. "Classification of Building Damage Using a Novel Convolutional Neural Network Based on Post-Disaster Aerial Images." *Sensors* 22 (15): 5920. https://doi.org/10.3390/s22155920.

Huang, T., Z. Wu, J. Wu, J. Hwang, and R. Rajagopal. 2024b. "City-Pulse: Fine-Grained Assessment of Urban Change with Street View Time Series." *Proceedings of the AAAI Conference on Artificial Intelligence* 38 (20): 22123–22131. https://doi.org/10.1609/aaai.v38i20.30216.

Huang, H., X. Yan, Y. Zheng, J. He, L. Xu, and D. Qin. 2024a. "Multi-View Stereo Algorithms Based on Deep Learning: A Survey." *Multimedia Tools and Applications* 84:2877–2908. https://doi.org/10.1007/s11042-024-20464-9.

Jiang, S., Y. Ma, W. Jiang, and Q. Li. 2024. "Efficient Structure from Motion for UAV Images via Anchor-Free Parallel Merging." *ISPRS Journal of Photogrammetry and Remote Sensing* 211:156–170. https://doi.org/10.1016/j.isprsjprs.2024.04.005.

Jozi, D., N. Shirzad-Ghaleroudkhani, G. Luhadia, S. Abtahi, and M. Gül. 2024. "Rapid Post-disaster Assessment of Residential Buildings Using Unmanned Aerial Vehicles." *International Journal of Disaster Risk Reduction* 111:104707. https://doi.org/10.1016/j.ijdrr.2024.104707.

Kang, D., and Y. Cha. 2018. "Autonomous UAVs for Structural Health Monitoring Using Deep Learning and an Ultrasonic Beacon System with geo-Tagging." *Computer-Aided Civil and Infrastructure Engineering* 33 (10): 885–902. https://doi.org/10.1111/mice.12375.

Kang, D., and Y. Cha. 2022. "Efficient Attention-Based Deep Encoder and Decoder for Automatic Crack Segmentation." *Structural Health Monitoring* 21 (5): 2190–2205. https://doi.org/10.1177/14759217211053776.

Kekec, T., A. Yildirim, and M. Unel. 2014. "A new Approach to Real-Time Mosaicing of Aerial Images." *Robotics and Autonomous Systems* 62 (12): 1755–1767. https://doi.org/10.1016/j.robot.2014.07.010.

Khaloo, A., D. Lattanzi, K. Cunningham, R. Dell'Andrea, and M. Riley. 2017. "Unmanned Aerial Vehicle Inspection of the Placer River Trail Bridge through Image-Based 3D Modelling." *Structure and Infrastructure Engineering* 14 (1): 124–136. https://doi.org/10.1080/15732479.2017.1330891.

Kharroubi, A., Z. Ballouch, R. Hajji, A. Yarroudh, and R. Billen. 2024. "Multi-context Point Cloud Dataset and Machine Learning for Railway Semantic Segmentation." *Infrastructures* 9 (4): 71. https://doi.org/10.3390/infrastructures9040071.

Kim, G., and Y. Cha. 2024. "3D Pixelwise Damage Mapping Using a Deep Attention Based Modified Nerfacto." *Automationin Construction* 168:105878. https://doi.org/10.1016/j.autcon.2024.105878.

Kolbeinsson, B., and K. Mikolajczyk. 2024. "DDOS: The Drone Depth and Obstacle Segmentation Dataset." *2024 IEEE/ CVF Conference on Computer Vision and Pattern Recognition Workshops*, 7328–7337. https://doi.org/10.1109/CVPRW63382.2024.00728.

Knöbelreiter, P., C. Vogel, and T. Pock. 2018. "Self-Supervised Learning for Stereo Reconstruction on Aerial Images." IGARSS 2018- 2018 IEEE International Geoscience and Remote Sensing Symposium, 4379–4382. https://doi.org/10.1109/IGARSS.2018.8518316.

Korhonen, Veera. 2024. Natural disasters in the U.S. - Statistics & Facts.

Koszyk, J., A. Jasińska, K. Pargieła, A. Malczewska, K. Grzelka, A. Bieda, and Ł Ambroziński. 2024. "Semantic Segmentation-Driven Integration of Point Clouds from Mobile Scanning Platforms in Urban Environments." *Remote Sensing* 16 (18): 3434https://doi.org/10.3390/rs16183434.

Kumar Jagatheesaperumal, S., M. M. Hassan, M. R. Hassan, and G. Fortino. 2024. "The Duo of Visual Servoing and Deep Learning-Based Methods for Situation-Aware Disaster Management: A Comprehensive Review." *Cognitive Computation* 16:2756–2778. https://doi.org/10.1007/s12559-024-10290-4.

Li, S., and H. Tang. 2018. "Building Damage Extraction Triggered by Earthquake Using the UAV Imagery." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XLII-3, 929–936. https://doi.org/10.5194/isprs-archives-XLII-3-929-2018.

Lin, M., G. Yang, and H. Zhang. 2023. "Transition Is a Process: Pair-to- Video Change Detection Networks for Very High Resolution Remote Sensing Images." *IEEE Transactions on Image Processing* 32:57–71. https://doi.org/10.1109/TIP.2022.3226418.

Liu, B., H. Chen, K. Li, and M. Yang. 2024a. "Transformer-Based Multimodal Change Detection with Multitask Consistency Constraints." *Information Fusion* 108:102358. https://doi.org/10.1016/j.inffus.2024.102358.

Liu, C., J. Zhao, C. Zhu, X. Xia, and H. Long. 2024b. "MECFNet: Reconstruct Sharp Image for UAV-Based Crack Detection." *IEEE Transactions on Intelligent Transportation Systems* 25 (10): 15016–15028. https://doi.org/10.1109/TITS.2024.3401754.

Liu, X., W. Zhu, X. Lian, and X. Xu. 2023. "Monitoring Mining Surface Subsidence with Multi-Temporal Three-Dimensional Unmanned Aerial Vehicle Point Cloud." *Remote Sensing* 15 (2): 374. https://doi.org/10.3390/rs15020374.

Lowe, David G. 2004. "Distinctive Image Features from Scale-Invariant Keypoints." *International Journal of Computer Vision* 60:91–110. https://doi.org/10.1023/B:VISI.0000029664.99615.94.

Luo, W., S. Gan, X. Yuan, S. Gao, R. Bi, C. Chen, W. He, and L. Hu. 2023b. "Repeated UAV Observations and Digital Modeling for Surface Change Detection in Ring Structure Crater Margin in Plateau." *Drones* 7 (5): 298. https://doi.org/10.3390/drones7050298.

Luo, S., H. Li, Y. Li, C. Shao, H. Shen, and L. Zhang. 2023a. "An Evolutionary Shadow Correction Network and a Benchmark UAV Dataset for Remote Sensing Images." *IEEE Transactions on Geoscience and Remote Sensing* 61:1–14. https://doi.org/10.1109/TGRS.2023.3295450.

Lyu, M., Y. Zhao, C. Huang, and H. Huang. 2023. "Unmanned Aerial Vehicles for Search and Rescue: A Survey." *Remote Sensing* 15 (13): 3266. https://doi.org/10.3390/rs15133266.

Madhuanand, L., F. Nex, and M. Yang. 2021. "Self-Supervised Monocular Depth Estimation from Oblique UAV Videos." *ISPRS Journal of Photogrammetry and Remote Sensing* 176:1–14. https://doi.org/10.1016/j.isprsjprs.2021.03.024.

Mandirola, M., C. Casarotti, S. Peloso, I. Lanese, E. Brunesi, and I. Senaldi. 2022. "Use of UAS for Damage Inspection and Assessment of Bridge Infrastructures." *International Journal of Disaster Risk Reduction* 72:102824. https://doi.org/10.1016/j.ijdrr.2022.102824.

Mao, Y., H. Bi, L. Xu, K. Chen, Z. Wang, X. Sun, and K. Fu. 2024. "SDL-MVS: View Space and Depth Deformable Learning Paradigm for Multiview Stereo Reconstruction in Remote Sensing." *IEEE Transactions on Geoscience and Remote Sensing* 62:1–18. https://doi.org/10.1109/TGRS.2024.3464574.

Marsocci, V., V. Coletta, R. Ravanelli, S. Scardapane, and M. Crespi. 2023. "Inferring 3D Change Detection from Bitemporal Optical Images." *ISPRS Journal of Photogrammetry and Remote Sensing* 196:325–339. https://doi.org/10.1016/j.isprsjprs.2022.12.009.

McEnroe, P., S. Wang, and M. Liyanage. 2022. "A Survey on the Convergence of Edge Computing and AI for UAVs: Opportunities and Challenges." *IEEE Internet of Things Journal* 9 (17): 15435–15459. https://doi.org/10.1109/JIOT.2022.3176400.

Melo, A., M. Pinto, L. Honório, F. Dias, and J. Masson. 2020. "3D Correspondence and Point Projection Method for Structures Deformation Analysis." *IEEE Access* 8:177823–177836. https://doi.org/10.1109/ACCESS.2020.3027205.

Miao, Z., X. Ji, T. Okazaki, and N. Takahashi. 2021. "Pixel-Level Multicategory Detection of Visible Seismic Damage of Reinforced Concrete Components." *Computer-aided Civil and Infrastructure Engineering* 36 (5): 620–637. https://doi.org/10.1111/mice.12667.

Mildenhall, B., P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng. 2020. "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis." Computer Vision - ECCV 2020, 405–421. https://doi.org/10.1145/3503250.

Mirzazade, A., C. Popescu, T. Blanksvärd, and B. Täljsten. 2021. "Workflow for Off-Site Bridge Inspection Using Automatic Damage Detection-Case Study of the Pahtajokk Bridge." *Remote Sensing* 13 (14): 2665. https://doi.org/10.3390/rs13142665.

Munawar, H., F. Ullah, A. Heravi, M. Thaheem, and A. Maqsoom. 2022. "Inspecting Buildings Using Drones and Computer Vision: A Machine Learning Approach to Detect Cracks and Damages." *Drones* 6 (1): 5. https://doi.org/10.3390/drones6010005.

Nath, N., C. Cheng, and A. Behzadan. 2022. "Drone Mapping of Damage Information in GPS-Denied Disaster Sites." *Advanced Engineering Informatics* 51:101450. https://doi.org/10.1016/j.aei.2021.101450.

Ngeljaratan, L., E. Bas, and M. Moustafa. 2024. "Unmanned Aerial Vehicle-Based Structural Health Monitoring and Computer Vision-Aided Procedure for Seismic Safety Measures of Linear Infrastructures." *Sensors* 24 (5): 1450. https://doi.org/10.3390/s24051450.

Rahnemoonfar, M., T. Chowdhury, and R. Murphy. 2023. "RescueNet: A High Resolution UAV Semantic Segmentation Dataset for Natural Disaster Damage Assessment." *Scientific Data* 10:913. https://doi.org/10.1038/s41597-023-02799-4.

Reduction, Disaster, Emergency Management (DREM), National Disaster Reduction Centre of China (NDRCC), International Federation of Red Cross, Red Crescent Societies (IFRC), and Beijing Normal University. 2023. *2022 Global Natural Disaster Assessment Report*. https://www.preventionweb.net/publication/2022-global-natural-disaster-assessment-report.

Rizzoli G., F. Barbato, M. Caligiuri, and P. Zanuttigh. 2023. "Syndrone-Multi-Modal Uav Dataset for Urban Scenarios." *2023 IEEE/CVF International Conference on Computer Vision*, 2210–2220. https://doi.org/10.1109/ICCVW60793.2023.00235.

Rublee, E., V. Rabaud, K. Konolige, and G. Bradski. 2011. "ORB: An Efficient Alternative to SIFT or SURF." 2011 international Conference on Computer Vision, 2564–2571. https://doi.org/10.1109/ICCV.2011.6126544.

San, J., C. Jiang, and W. Jiang. 2020. "Efficient Structure from Motion for Large- Scale UAV Images: A Review and a Comparison of SfM Tools." *ISPRS Journal of Photogrammetry and Remote Sensing* 167:230–251. https://doi.org/10.1016/j.isprsjprs.2020.04.016.

Sayed Ishaq, D., and A. Uğur. 2021. "Accuracy of Unmanned Aerial Systems Photogrammetry and Structure from Motion in Surveying and Mapping: A Review." *Journal of the Indian Society of Remote Sensing* 49:1997–2017. https://doi.org/10.1007/s12524-021-01366-x.

Shirzad-Ghaleroudkhani, N., D. Jozi, G. Luhadia, S. Abtahi, and M. Gül. 2024. "UAV-Based Post-Disaster Assessment of Residential Buildings Using Image Processing." Proceedings of the Canadian Society for Civil Engineering Annual Conference 2023 13: 45–57. https://doi.org/10.1007/978-3-031-61539-94.

Stambler A., G. Sherwin, and P. Rowe. 2019. "Detection and Reconstruction of Wires Using Cameras for Aircraft Safety Systems." *2019 International Conference on Robotics and Automation*, 697–703. https://doi.org/10.1109/ICRA.2019.8793526.

Stathopoulou, K., R. Battisti, D. Cernea, A. Georgopoulos, and F. Remondino. 2023. "Multiple View Stereo with Quadtree-Guided Priors." *ISPRS Journal of Photogrammetry and Remote Sensing* 196:197–209. https://doi.org/10.1016/j.isprsjprs.2022.12.013.

Sun, S., L. Mu, L. Wang, and P. Liu. 2022. "L-UNet: An LSTM Network for Remote Sensing Image Change Detection." *IEEE Geoscience and Remote Sensing Letters* 19:1–5. https://doi.org/10.1109/LGRS.2020.3041530.

Turki, H., D. Ramanan, and M. Satyanarayanan. 2022. "Mega-NeRF: Scalable Construction of Large-Scale NeRFs for Virtual Fly-Throughs." 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 12912–12921. https://doi.org/10.1109/CVPR52688.2022.01258.

Wang W., D. Zhu, X. Wang, Y. Hu, Y. Qiu, C. Wang, Y. Hu, A. Kapoor, and S. Scherer. 2020. "Tartanair: A Dataset to Push the Limits of Visual Slam." *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 4909–4916. https://doi.org/10.1109/IROS45743.2020.9341801.

Wang, X., C. Demartino, Y. Narazaki, G. Monti, and B. Spencer. 2023a. "Rapid Seismic Risk Assessment of Bridges Using UAV Aerial Photogrammetry." *Engineering Structures* 279:115589. https://doi.org/10.1016/j.engstruct.2023.115589.

Wang, Y., X. Jing, W. Chen, H. Li, Y. Xu, and Q. Zhang. 2023. "Geometry-Informed Deep Learning-Based Structural Component Segmentation of Post-Earthquake Buildings." *Mechanical Systems and Signal Processing* 188:110028. https://doi.org/10.1016/j.ymssp.2022.110028.

Wang, Q., W. Jing, K. Chi, and Y. Yuan. 2024. "Cross-Difference Semantic Consistency Network for Semantic Change Detection." *IEEE Transactions on Geoscience and Remote Sensing* 62:1–12. https://doi.org/10.1109/TGRS.2024.3386334.

Wang, Z., Y. Zhang, L. Luo, K. Yang, and L. Xie. 2023b. "An End-to-End Point-Based Method and a New Dataset for Street-Level Point Cloud Change Detection." *IEEE Transactions on Geoscience and Remote Sensing* 61:1–15. https://doi.org/10.1109/TGRS.2023.3295386.

Waqas, A., D. Kang, and Y. Cha. 2024. "Deep Learning-Based Obstacle-Avoiding Autonomous UAVs with Fiducial Marker-Based Localization for Structural Health Monitoring." *Structural Health Monitoring* 23 (2): 971–990. https://doi.org/10.1177/14759217231177314.

Wen, Y., Z. Zhang, Q. Cao, and G. Niu. 2024. "TransC-GD-CD: Transformer-Based Conditional Generative Diffusion Change Detection Model." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 17:7144–7158. https://doi.org/10.1109/JSTARS.2024.3373201.

Xiang, X., H. Hu, Y. Ding, Y. Zheng, and S. Wu. 2023. "GC-YOLOv5s: A Lightweight Detector for UAV Road Crack Detection." *Applied Sciences* 13 (19): 11030. https://doi.org/10.3390/app131911030.

Xing, J., Y. Liu, and G. Zhang. 2023. "Improved YOLOV5-Based UAV Pavement Crack Detection." *IEEE Sensors Journal* 23 (14): 15901–15909. https://doi.org/10.1109/JSEN.2023.3281585.

Yang K., G. S. Xia, Z. Liu, B. Du, W. Yang, M. Pelillo, and L. Zhang. 2020. "Semantic Change Detection with Asymmetric Siamese Networks." *arXiv preprint arXiv:2010.05687*.

Yang, Y., G. Yuan, and J. Li. 2024. "SFFNet: A Wavelet-Based Spatial and Frequency Domain Fusion Network for Remote Sensing Segmentation." *IEEE Transactions on Geoscience and Remote Sensing* 62:1–17. https://doi.org/10.1109/TGRS.2024.3427370.

Yao, F., C. Lan, L. Wang, H. Wan, T. Gao, and Z. Wei. 2024. "GNSS-Denied Geolocalization of UAVs Using Terrain-Weighted Constraint Optimization." *International Journal of Applied Earth Observation and Geoinformation* 135:104277. https://doi.org/10.1016/j.jag.2024.104277.

Zahs, V., A. Katharina, K. Julia, S. Alexander, and H. Bernhard. 2023. "Classification of Structural Building Damage Grades from Multi-temporal Photogrammetric Point Clouds Using a Machine Learning Model Trained on Virtual Laser Scanning Data." *International Journal of Applied Earth Observation and Geoinformation* 122:103406. https://doi.org/10.1016/j.jag.2023.103406.

Zhai, Y., W. Li, T. Xian, X. Jia, H. Zhang, Z. Tan, J. Zhou, J. Zeng, and C. Chen. 2024. "CAS-Net: Comparison-Based Attention Siamese Network for Change Detection With an Open High-Resolution UAV Image Dataset." *IEEE Transactions on Geoscience and Remote Sensing* 62:1–17. https://doi.org/10.1109/TGRS.2024.3386918.

Zhang, S., Y. He, Y. Gu, Y. He, H. Wang, H. Wang, R. Yang, T. Chady, and B. Zhou. 2024b. "UAV Based Defect Detection and Fault Diagnosis for Static and Rotating Wind Turbine Blade: A Review." *Nondestructive Testing and Evaluation* 40 (4): 1691–1729. https://doi.org/10.1080/10589759.2024.2395363.

Zhang, C., and J. Liu. 2024. "Change Detection with Incorporating Multi-Constraints and Loss Weights." *Engineering Applications of Artificial Intelligence* 133:108163. https://doi.org/10.1016/j.engappai.2024.108163.

Zhang, H., Y. Reuland, J. Shan, and E. Chatzi. 2024a. "Post-earthquake Structural Damage Assessment and Damage State Evaluation for RC Structures with Experimental Validation." *Engineering Structures* 304:117591. https://doi.org/10.1016/j.engstruct.2024.117591.

Zhang, F., T. Yang, L. Liu, B. Liang, Y. Bai, and J. Li. 2021. "Image-Only Real-Time Incremental UAV Image Mosaic for Multi-strip Flight." *IEEE Transactions on Multimedia* 23:1410–1425. https://doi.org/10.1109/TMM.2020.2997193.

Zhao, S., F. Kang, J. Li, and C. Ma. 2021. "Structural Health Monitoring and Inspection of Dams Based on UAV Photogrammetry with Image 3D Reconstruction." *Automation in Construction* 130:103832. https://doi.org/10.1016/j.autcon.2021.103832.

Zhao, J., X. Zhang, C. Gao, X. Qiu, Y. Tian, Y. Zhu, and W. Cao. 2019. "Rapid Mosaicking of Unmanned Aerial Vehicle (UAV) Images for Crop Growth Monitoring Using the SIFT Algorithm." *Remote Sensing* 11 (10): 1226. https://doi.org/10.3390/rs11101226.

Zhao, Y., L. Zhou, X. Wang, F. Wang, and G. Shi. 2023. "Highway Crack Detection and Classification Using UAV Remote Sensing Images Based on CrackNet and Crack Classification." *Applied Sciences* 13 (12): 7269. https://doi.org/10.3390/app13127269.

Zheng, Z., Y. Zhong, L. Zhang, M. Burke, D. Lobell, and S. Ermon. 2024. "Towards Transferable Building Damage Assessment via Unsupervised Single-Temporal Change Adaptation." *Remote Sensing of Environment* 315:114416. https://doi.org/10.1016/j.rse.2024.114416.