UAV Surveying for Emergency Facility Construction: Recent Advances in Data Collection and Processing

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Abstract –

This study provides a review of the literature regarding unmanned aerial vehicles (UAV) surveying for emergency facility construction, with a focus on data collection and processing methods. Synthesizing publications between 2016 and 2025, this study categorizes the applications of visible-light cameras, thermal infrared cameras, light detection and ranging (LiDAR), and multi-source sensing configurations. Discussion of data processing highlights key methodologies in image analysis, point clouds, and multimodal fusion, emphasizing semantic segmentation, three-dimensional (3D) reconstruction, and simultaneous localization and mapping (SLAM) as pivotal for transforming raw data into geospatial information. Reported applications focus on natural disaster scenarios and support tasks such as survivor search, route planning, and emergency facility site selection and assessment. These findings provide a basis for the future development of UAV-integrated emergency response systems.

Keywords –

UAV; Emergency Facility Construction; Data Collection; Data Processing

1 Introduction

The global increase in the frequency and severity of disasters, particularly large-scale flooding, earthquakes, and extreme weather events, has placed critical infrastructure and human lives at escalating risk. In the immediate aftermath of such events, priorities shift toward humanitarian relief and the rapid restoration of essential services. Central to these efforts is the timely construction of emergency facilities such as temporary shelters, logistics hubs, and provisional access routes [1]. Effective planning for these facilities requires high-accuracy geospatial information. Yet, conventional ground-based surveying techniques are infeasible in disaster contexts, where access is restricted, terrain is unstable, and time is of the essence [2]. Insufficient terrain mapping can lead to suboptimal or even hazardous facility placement, increasing exposure to secondary risks (e.g., renewed flooding, landslides), and delaying aid delivery.

Unmanned aerial vehicles (UAV) have been adopted for rapid disaster response [3]. Their deployment in Hurricane Wilma [4] and the Lushan earthquake in China [5] demonstrated the value of aerial assessments for identifying damaged areas, guiding rescue teams, and supporting situational awareness. Existing reviews have documented UAV contributions across disaster management, search and rescue, damage detection [6, 7], and civil infrastructure monitoring[8]. However, these applications emphasize visual inspection and reconnaissance rather than the acquisition of high-precision geospatial information. The transition from general aerial awareness to reliable mapping introduces challenges, including stringent accuracy requirements, robust sensor calibration, complex data processing, and the need to operate under hazardous environmental conditions [9].

Recent technological advances are beginning to mitigate these limitations. UAV equipped with high-resolution sensors now facilitate the rapid generation of Digital Elevation Models (DEMs), orthophotos, and other high-fidelity geospatial products [10]. Nevertheless, the literature on UAV-based mapping specifically tailored to emergency facility construction remains fragmented, with limited systematic synthesis of technologies, methodologies, and validated practices

This study addresses this gap by synthesizing research from the past decade, guided by two core research questions:

(1) What recent advances in UAV sensing techniques improve data collection accuracy and speed in challenging environments?

(2) What advanced data processing methods ensure the geometric accuracy required for emergency facility construction?

The remainder of this paper is structured as follows: Section 2 details the methodology for the literature selection and analysis. Sections 3 and 4 present recent advances in UAV-based data collection and processing, respectively. Section 5 summarizes the paper and highlights research gaps for future work.

2 Literature Search and Bibliometric Analysis

This study employs bibliometric analysis to evaluate English-language literature concerning UAV-based mapping for emergency facility construction published between 2016 and 2025. The search targeted core databases across engineering and technology, geoinformation science, and disaster management. A multi-dimensional search strategy was implemented, integrating UAV-related terms (e.g., unmanned aerial vehicle, UAV, drone); emergency facility-related terms (e.g., emergency infrastructure, disaster infrastructure, temporary facility, relief camp, emergency facility); and disaster scenario-related terms (e.g., disaster relief, post-disaster, post-disaster construction). To ensure a comprehensive dataset, subject terms, keywords, and abstracts were cross-referenced, initially yielding over 100 publications. Following a rigorous screening process to exclude papers with weak relevance to "core UAV mapping technologies" or "practical applications," 93 publications were retained. These were analyzed using CiteSpace for keyword co-occurrence and clustering.

Figure 1 presents the keyword co-occurrence network. High-frequency terms such as "disaster management" and "disaster response" delineate the operational context of emergency facility construction. The network also indicates that deep learning and computational modeling are prominent technical approaches. Because emergency facility construction relies on high-precision geospatial information, deep learning is used for image recognition, target segmentation, and disaster-feature extraction, while computational modeling, mainly referring to three-dimensional (3D) reconstruction, supports terrain simulation and facility layout optimization.

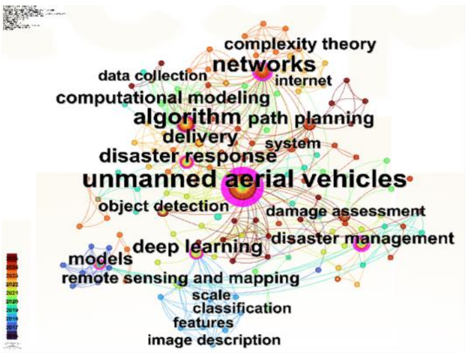

Figure 1. Keyword co-occurrence network

Using the log-likelihood ratio (LLR) algorithm in CiteSpace, seven clusters were identified (see Figure 2). The clustering results yield Q = 0.7455 (> 0.3) and S = 0.9473 (> 0.7), suggesting good separation among clusters and consistency within clusters. The data sensing cluster covers remote data collection and air–ground hybrid data collection, reflecting developments in data acquisition and sensor integration. The data processing cluster includes remote-sensing semantic segmentation and vision-based methods. The practical application cluster includes disaster rescue, security applications, and hazard-mitigation planning, reflecting the use of UAV in emergency facility construction.

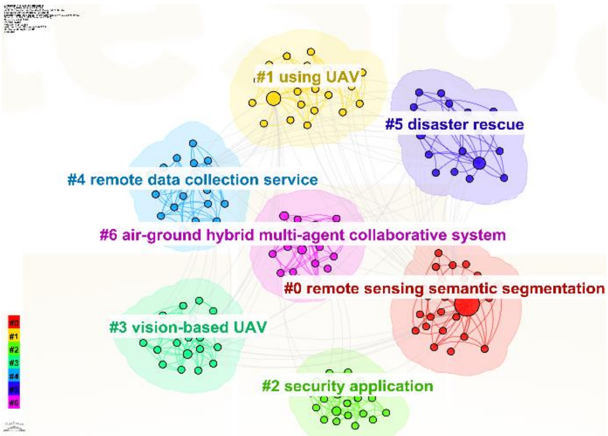

Figure 2. Keyword clustering map

3 Data Collection techniques

Emergency facility construction requires survey data with high accuracy and short acquisition cycles, and the ability to accommodate changing disaster conditions. To meet these needs, UAV-based sensing techniques are used to collect different types of data.

3.1 Optical Sensing Technique

Optical sensors capture high-resolution spectral data essential for topographic mapping, feature identification, and damage assessment in emergency contexts.

3.1.1 Visible-light Camera

Visible-light cameras are widely used optical sensors. Eltner et al. [11] used a single UAV-mounted camera to capture optical imagery of small-scale topographic features, including slope micro-relief and debris-flow surface textures. Prokešová et al. [12] extended this approach to larger disaster settings by collecting imagery of landslide-prone areas. Galve et al. [13] investigated debris-flow and landslide sites along Spain's A-7 highway using an UAV equipped with an ultra-high-resolution camera to collect multi-temporal imagery. To address challenges in pavement deformation measurement in landslide terrain, Cardenal et al. [14] used a mirrorless interchangeable-lens camera and increased pixel density to support precise deformation measurements. However, visible-light imaging is sensitive to environmental interference. Atmospheric disturbances such as rain and fog can severely degrade image clarity and texture detail, or even obstruct imaging entirely. Furthermore, because visible-light cameras primarily capture planar data, they may not able to provide precise 3D spatial coordinates in occluded disaster environments.

3.1.2 Thermal Infrared Camera

Thermal infrared cameras detect the infrared radiation emitted by objects, translating temperature differentials into thermal signatures. This capability allows them to function in low-visibility conditions, including total darkness or light fog. Hoshino et al. [15] used thermal infrared imaging to exploit radiance differences between human bodies and surrounding backgrounds for victim detection and localization. This mitigates limitations of visible-light imaging in low light or smoke. Similarly, Dong et al. [16] mounted thermal cameras on UAV to collect data on victim postures and occlusions, which can improve survivor detection in earthquake rubble. Tavasoli et al. [17] demonstrated that thermal signatures can be used to map the spatial distribution of victims to prioritize emergency response. However, thermal infrared cameras typically feature lower spatial resolution than visible-light cameras.

3.2 Light Detection and Ranging (LiDAR)

Unlike optical sensors, LiDAR acquires dense 3D point clouds by emitting laser pulses and measuring returned signals. This provides 3D geometric detail along with spatial coordinates and distance measurements. LiDAR performance is largely independent of ambient lighting, making it suitable for nocturnal operations. Additionally, its multi-echo capabilities allow it to penetrate partial vegetation or debris cover, maintaining high ranging accuracy where optical sensors fail. Pellicani et al. [18] used LiDAR to collect high-density point clouds in landslide areas. Zhou et al.[19] used pre- and post-hurricane LiDAR point clouds to quantify damage to residential buildings, enabling assessment without additional contact with unstable structures during emergency operations. Despite these advantages, LiDAR systems remain high-cost, and their ranging precision can still be attenuated by extreme weather conditions.

3.3 Multi-Source Sensor Fusion

Table 1 summarizes the strengths and limitations of visible-light cameras, thermal infrared cameras, and LiDAR. In applications, these sensors are often combined to address the limitations of any single sensor.

Table1 Functions, limitations and factors of UAV-borne sensor types

Sensing type		Functions	Limitations	Factors
Optical sensor	Visible light camera	2D images	Poor adaptability to low-light and harsh weather; Only 2D information	Sunlight; Rainfall; Fog
	Thermal infrared camera	2D thermal radiation images	Low spatial resolution; No texture information	Heavy fog; Overcast and rainy; Severe dust
LiDAR sensor	LiDAR	3D spatial information	High cost; No spectral and thermal information	Heavy fog; Overcast and rainy
Multi-source sensor	Visible light camera+ Thermal infrared camera	2D texture and thermal radiation information	Dominated by 2D information; Limited data accuracy	Vegetation occlusion; Heavy fog
	Visible light camera+ LiDAR	3D spatial and 2D texture information	High cost; Poor adaptability to harsh weather	Heavy fog; Heavy rain
	Thermal infrared camera+ LiDAR	3D spatial and thermal radiation information	High cost; No texture information	Heavy fog; Overcast and rainy
	Visible light camera + Thermal infrared camera +LiDAR	3D spatial, 2D texture and thermal radiation information	Highest cost; Complex data fusion process	Extreme harsh weather (e.g., severe rainstorm and heavy fog)

Sensor fusion approaches combine sensors according to the data requirements of emergency surveys, disaster monitoring, and related tasks during raw data acquisition. Mineo et al. [20] used visible-light imagery to reconstruct the 3D geometry and surface texture of landslides and integrated thermal infrared data to identify thermal anomalies in rock and soil. This combination supports characterization of landslide morphology while capturing subsurface- or surface-related thermal signals. Yu et al. [21] improved post-earthquake facility safety assessment by combining visible-light imagery of surface damage with LiDAR-derived 3D point clouds at millimeter-level accuracy. Cella et al. [22] used thermal infrared imaging to locate survivors and identify high-temperature hazards, while using LiDAR to generate 3D models to support spatial context in rescue operations. Shen et al. [23] integrated visible-light data for texture-based damage detection, thermal infrared data for thermal anomaly detection, and LiDAR for 3D geometric reconstruction, covering multiple information needs in post-disaster surveys. Overall, multi-source sensor fusion provides task-specific raw datasets that support subsequent data processing.

4 Data Processing Methods

Raw datasets acquired in disaster zones are typically voluminous, heterogeneous, and redundant. Data processing in this field focuses primarily on image and point cloud data.

4.1 Image Data Processing Methods

Processing of optical imagery emphasizes texture information and semantic attributes, and commonly uses deep learning to convert raw imagery into structured outputs. This section focuses on semantic segmentation and 3D reconstruction.

4.1.1 Deep Learning-based Image Semantic Segmentation

To improve semantic segmentation accuracy for UAV imagery, Zhou et al. [24] proposed a lightweight UAV frequency-aware and attention-enhanced network. Sui et al. [25] proposed the typical disaster bearing objects segmentation network semantic segmentation model, which can supported disaster target recognition in flood-related UAV imagery. To further enhance the specificity and precision of semantic segmentation, Stache et al. [26] combined a deep learning–based accuracy model with a UAV adaptive path-planning algorithm to link segmentation performance with data collection strategy, supporting decisions in emergency facility planning. However, the efficacy of these models remains contingent upon image quality, and the high computational overhead often hinders the real-time performance critical for immediate response.

4.1.2 3D Reconstruction using Structure from Motion (SfM)/Multiview Stereo (MVS)

With advances in computer vision, integrated SfM/MVS pipelines are widely used for 3D reconstruction from UAV imagery. These methods extract image feature points, estimate camera poses, generate sparse point clouds, and then perform dense reconstruction [27]. To mitigate computational latency, Zhang et al. [28] proposed an end-to-end latency optimization strategy that reduced modeling delay by about 40% while maintaining reconstruction accuracy. Wang et al. [29] used region-based parallel reconstruction and plane-detection optimization to improve efficiency and model completeness without requiring high-performance hardware. Despite these gains, SfM/MVS remains largely an offline, batch-processing approach, making it less suitable for incremental mapping in dynamic environments.

4.1.3 3D Reconstruction using Visual Simultaneous Localization and Mapping (SLAM)

Compared with SfM/MVS, visual SLAM supports real-time localization and incremental mapping, which aligns with the time constraints of emergency data processing [30]. To address accuracy and timeliness in post-disaster UAV surveying and mapping, Bi et al. [31] developed a UAV visual SLAM processing system based on ORB-SLAM2, improving both accuracy and real-time performance. Huo et al. [32] extended the workflow to include image correction and stitching, as well as obstacle detection. They further applied map fusion and path-planning algorithms to connect While visual SLAM aligns well with the time-sensitive nature of emergency response, it frequently struggles with feature-point matching in highly dynamic environments or areas with dense obstacles.

4.2 Point Cloud Data Processing Methods

Point clouds are the primary 3D data product collected by LiDAR, and their processing affects the accuracy of emergency surveying and mapping. This section reviews point cloud semantic segmentation and LiDAR-SLAM–based 3D reconstruction.

4.2.1 Deep Learning-based Point Cloud Semantic Segmentation

Deep learning methods for LiDAR point cloud semantic segmentation use neural networks to extract point-level features and assign category labels, providing semantic information for tasks such as 3D scene understanding and emergency mapping. Atik et al. [33] proposed the SegUNet3D ensemble approach, which converts point clouds into distance images and extracts geometric features. Li et al. [34] addressed the trade-off between data complexity and processing efficiency in large-scale segmentation by proposing the slight filter learning network. However, a persistent challenge in this area is the heavy reliance on large, annotated datasets, which are often unavailable in unique disaster contexts.

4.2.2 LiDAR-SLAM–based 3D reconstruction

Compared with image-based reconstruction, LiDAR-SLAM does not require inferring 3D structure from 2D pixels. Instead, it uses the inherent spatial coordinates of point clouds to support geometric reconstruction and mapping [35]. Kaul [36] developed a compact quadcopter-based reconstruction method that generates dense point cloud maps using continuous-time SLAM. Real-time performance remains a constraint in many deployments. Mojtaba et al. [37] proposed a low-latency LiDAR-SLAM framework for incremental 3D reconstruction using lightweight point cloud segmentation and parallel matching, targeting high-dynamic, small-scale scenarios. Ćwian et al. [38] used geometric feature representations and factor-graph optimization to improve accuracy and efficiency in large-scale reconstruction. Together, these studies illustrate how LiDAR-SLAM pipelines can be adapted to different operational settings. However, positioning accuracy is often compromised in feature-sparse environments, as the scarcity of structural landmarks limits the algorithm's ability to maintain a stable spatial reference.

4.3 Processing Method for Fused Data

Image–point cloud fusion aims to combine complementary information: images provide texture and semantic cues, while point clouds provide 3D geometry. This section focuses on semantic fusion segmentation and SLAM-based 3D reconstruction using visual/LiDAR fusion.

4.3.1 Image–point cloud semantic fusion segmentation

Fusion-based segmentation methods vary by scenario and by the constraints of annotation, scale, and runtime. Dong et al. [39] proposed a parallel dual-stream (PD) network for semi-supervised semantic segmentation to reduce dependence on extensive labeled data in bimodal image–point cloud segmentation. Zhang et al. [40] proposed a deep learning-based image-point cloud fusion proposed an image–point cloud fusion scheme for large-scale 3D emergency scenarios to address segmentation error and missing information. Bultmann et al. [41] used a lightweight CNN with an embedded inference accelerator to integrate multimodal semantic cues into point cloud and image segmentation masks, producing global semantic maps suitable for time-constrained data processing. All these advances significantly improve the spatial resolution and reliability of semantic segmentation.

4.3.2 Visual/LiDAR SLAM–based 3D Reconstruction

By combining modalities, researchers can overcome the field-of-view limitations of LiDAR and the illumination sensitivity of vision [42]. Tong et al. [43] proposed a multi-sensor fusion framework that extends LiDAR-SLAM–based reconstruction to support emergency infrastructure surveying under complex conditions. Lou et al. [44] combined LiDAR with monocular vision to perform SLAM with 3D semantic reconstruction, addressing the limited semantic content of point clouds and supporting applications such as 3D surveying and post-disaster damage assessment. Consequently, this technology is well-suited for emergency infrastructure surveying and the assessment of building damage following seismic or fire events. However, the sophisticated fusion logic inherent in this technology imposes great demands on both algorithmic efficiency and hardware architectures.

5 Conclusion

This study applies bibliometric analysis to review research on UAV surveying and mapping for emergency facility construction published between 2016 and 2025. Using CiteSpace, keyword co-occurrence and clustering analyses were performed on 93 papers. The results indicate concentrations of research on sensor-based raw data acquisition and data processing methods based on deep learning and 3D reconstruction. For data acquisition, the review covers optical sensors (visible-light and thermal infrared cameras), LiDAR, and multi-sensor sensing/fusion configurations. For data processing, the literature centers on image data, point clouds, and multimodal fusion, with emphasis on semantic segmentation, 3D reconstruction, and SLAM-based approaches that convert raw data into geospatial information suitable for operational use.

The presented review focuses on sensors deployed on UAV platforms, related data processing methods, and their applications in emergency facility construction. Future work can assess endurance limitations and mitigation strategies to support sustained surveying and mapping in extended-duration operations, including landslide-prone and flood-affected areas.

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