Challenges in Capturing and Processing UAV based Photographic Data From Construction Sites

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Abstract– Construction industry is going through a paradigm shift where remote data collection approaches are replacing manual processes that are presently being followed in construction related activities. Unmanned Aerial Vehicles (UAV) are being engaged in various construction applications, like real-time supervision, progress evaluation, surveys, mapping, safety evaluations etc. The paper discusses some of the typical challenges related to operations, data acquisition, and post-processing of data collected using UAV when used in civil engineering applications. Issues related to obstructions, reflection, illuminations, lighting condition, blurred image data, inaccuracies in georeferenced image data etc. are discussed and possible solutions suggested based on a field study. A DJI Phantom 4 Pro V2.0 was used in data collection and the solutions for various issues identified from literature were evaluated and discussed based on collected field data. Feasible solutions for the above mentioned problems are also discussed and presented.

Keywords – Image Recordings; Recording Challenges; Construction Site Monitoring; Photogrammetry; UAV data processing challenges

1 Introduction

Over the last decade, use of Unmanned Arial Vehicles (UAV) in civilian activities have increased rapidly which ranges from infrastructure development to surveillance, goods delivery, agricultural, mining and many more [1]. Infrastructure development sector has started using UAVs in construction related activities like progress monitoring, surveying, aerial photography and surveillance, visual inspections, safety inspections, quantity take-off and estimation, defect and damage detection etc. [2]. Visual monitoring using camera equipped UAV is being used in earthwork measurement, damage assessment on structure, archeological site survey, safety planning and monitoring in high rise building construction, pavement distress detection, bridge inspections etc. [3, 4, 5, 6, 7, 8]. Utility of UAV data is not limited to construction monitoring at large, but can be extended for use in ortho-mapping, model development (digital elevation model, digital surface model), augmented reality models, 3D plans for structure, mesh model etc., using point cloud data generated from digital images [9, 10]. Use of UAV based photogrammetric data has now become the preferred option for civil engineers due to the diverse utility, accuracy, cost effectiveness and pace of data collection when compared to manual survey options used earlier. Efforts to adopt new and innovative technologies often encounter issues related to implementation, processing and data extraction which needs to be identified and solved in order to inculcate these approaches in construction activities. The objective of this study is to enumerate operational, data collection and post processing challenges while working with UAV data and to identify and evaluate feasible solutions from literature using field data.

2 Methodology

Challenges while working with UAV can broadly be classified into three categories (Figure 1). Section 3 of the paper addresses operational challenges which primarily include challenges in flight planning, like trajectory planning for cost minimization, avoiding data redundancy, occlusions, etc. [4]. Trajectory decisions often depend on the chosen flying height and required image overlay, details of which are included in section 3. Section 4 discusses the data collection issues related to occlusion, reflection, shadows etc. Issues encountered while working with blind spots, poor lighting conditions, similarity in object texture etc. during image processing is also discussed. Post-processing issues like blurred image, coordinate errors etc. are discussed briefly in section 5 of this paper.

3 Operational Issues

Flight planning for data collection involves trajectory planning, selection of data collection mode (manual or auto), deciding coverage area, selecting required image overlap etc., while accounting for logistical issues like, flight time, clearances, climatic issues etc. Trajectory is the path followed in data collection which often is the shortest route that can capture all required details along the project location. Selection of trajectory is often based

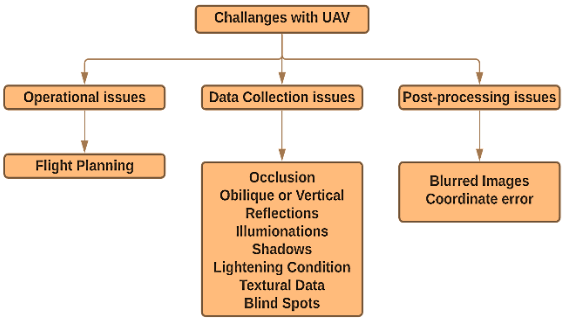

Figure 1. Classification of Challenges on working with UAV [4][5].

on optimizing coverage with minimal occlusions at the site. Even though trajectory is meant to cover maximum feature points of components falling in field of view (FOV) of UAV, pertinent details sometimes gets occluded as observed in schematic diagram (Figure 2). Semsch et al. (2009) in their study using multiple UAVs tried to identify the shortest trajectory that covers maximum feature points. After determining the starting points of UAVs, a surveillance algorithm which runs independently was used without any further coordination between the two trajectories. The occlusion-aware control mechanism developed during the study can be effective in trajectory planning for UAV-based data collection [11].

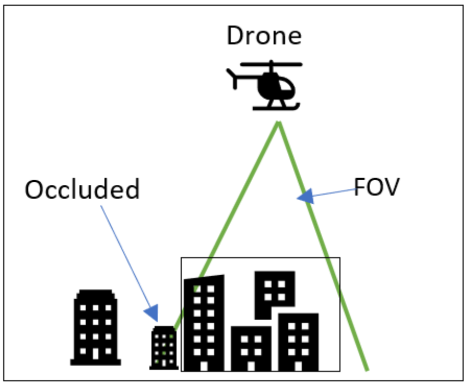

Figure 2. Graphical representation of occlusion in the FOV.

Parameters like shortest trajectory, battery constraints are also variables that need to be considered during trajectory planning which are often equipment specific due to variations in pay load capacity, flying time etc. Factors like lighting conditions, speed and shutter timing, and relative location of light source etc. need to be accounted for before actual data collection. Logistics issues like obtaining flying clearances, permissions based on the size and weight of different UAVs, etc. often varies across countries, details of which are explained and compared by Shrivastava et al. (2019). Information/details required while seeking permission for aerial survey from concerned authorities are also addressed by the authors [1].

4 Data Collection Issues

Issue related to data collection is discussed below with probable solutions.

4.1 Occlusions: Clutter, Auxiliary equipment's

Construction sites are often congested and cluttered with equipments which can lead to occlusions while collecting data remotely. Occlusions can be of two types (a) static occlusions and (b) dynamic occlusion [12, 13]. Static occlusions include missing data points due to stationary objects like formwork, scaffolding etc. whereas missing data points due to movement of workers, moving construction equipment's etc. can be considered as dynamic occlusions as illustrated in figure 2 and 3 [6] [7].

Construction sites are dynamic in nature which can lead to poor registration of dataset during progressive data collection. Given in Figure 3, is an issue related to dynamic occlusion while capturing data for foundation work at a construction site. While calculating quantity of earthwork from day 1 and day 2, occlusion due to auxiliary equipment in captured data set can lead to errors in estimated quantities. The data is also difficult to register with previously collected data set.

Figure 3. Example of dynamic occlusion

Images presented in Figure 4 explains issues related to dynamic occlusion in data collected for construction monitoring at site. Some of the ground control points (GCPs) is covered with construction materials, while few are occluded by clutters. Randomness, prompted by ease of construction, in positioning and arrangement of materials at construction site can lead to dynamic occlusions and difficulties in registration. Manual data processing techniques can address these errors to certain extent by eliminating identical objects with variable data sets from captured images or by registering only common points in both the data sets. However, issues may arise especially while using automated or unsupervised data processing algorithms.

Figure 4. (a) Marked GCP at construction site and (b) GCP occluded due to site activities.

Solution: Researchers presented different solutions to address dynamic occlusions ranging from 2D image processing to 3D photogrammetric techniques. The data collected for generating meshes and point cloud may have disturbances due to similarity in colors of objects at site, say, scaffoldings vs other structural components. Xu et al. [8] presented a solution for eliminating similar issues using fast point feature histogram (FPFH) and random forest classification algorithms. Point cloud data were classified with linear fitting algorithm and by using the signature of histograms of orientations (SHOT) algorithm to detect the shape to make the results more accurate. Golparvar-Fard et al. used an alternate approach where instead of the fixed camera location, photographs were captured in a random/unordered manner from nearby locations to avoid occlusion. Using structure from motion (SfM) technique thereafter helps removing small occlusion automatically, and the generated point clouds will not require any post-processing [9].

Tuttas et al. (2014) used construction logics and precedence charts, which assume completion of severely occluded construction elements based on the completion of dependent elements [10]. Another option in addressing dynamic occlusion is through point picking method where the selected points can be easily recognized and registered when executed manually. The approach works around locating common points in different images and use them as tie point for creating dense point cloud. Photogrammetric software's that can automate point picking approach are also available which saves time and can register more feature points. This method is further modified by Kim et al. (2013) using machine learning (ML) approach for comparing as-built vs. as-planned data sets. They used supervised learning Lalonde feature (which is a 3-dimensional vector that can be used to detect linearity, surface uniformity, and scatter of a 3D data set) and extracted structural components out from the data set. The assessment is based on the extracting data set of structural components only and neglecting feature points related to an auxiliary equipment causing occlusion [11].

Since construction sites and too complex and dynamic to handle, researchers have attempted many pre-processing and post-processing strategies to overcome clutter and dynamic occlusions while processing captured data. A simplified approach followed during data collection is to alter the time of data collection, subject to construction schedule, so that dynamic occlusion such as moving personnel and equipment can be avoided [6]. Another approach is to consider dynamic occlusion as a static if they are stationary in multiple data sets. A good example would be a welding machinery for steel construction held in one location for many days while working personal uses it for nearby locations. Approaches mentioned below to remove static occlusions can be applicable in this case.

Static occlusion on the other hand can be solved by adopting proper flight planning techniques and recording strategy. Trial and error approach are also being followed in many cases, where trial trajectories are used to identify areas where potential static occlusions may affect the registration. Trajectories are then modified to cover maximum details pertaining to objects relevant for assessment. A simulation study by Semsch et al. (2009) shows possibilities of managing occlusion, by testing trajectory even before flying. A good example would be AgentFly UAV simulation testbed which can be used to model a real world to create a framework for flight planning and collision avoidance [4]. Figure 5 shows a similar issue related to static occlusion in field which was overcome by using multiple trajectories.

Another approach in reducing registration inaccuracies is to ensure a large overlap between two data set, which helps increases the number of feature points. The feature point are higher in figure 6(b) as the number of occlusions reduced by changing the trajectory of the UAV [5].

Figure 5. (a) Occlusion due to structural component, (b) occlusion avoided using different UAV trajectory.

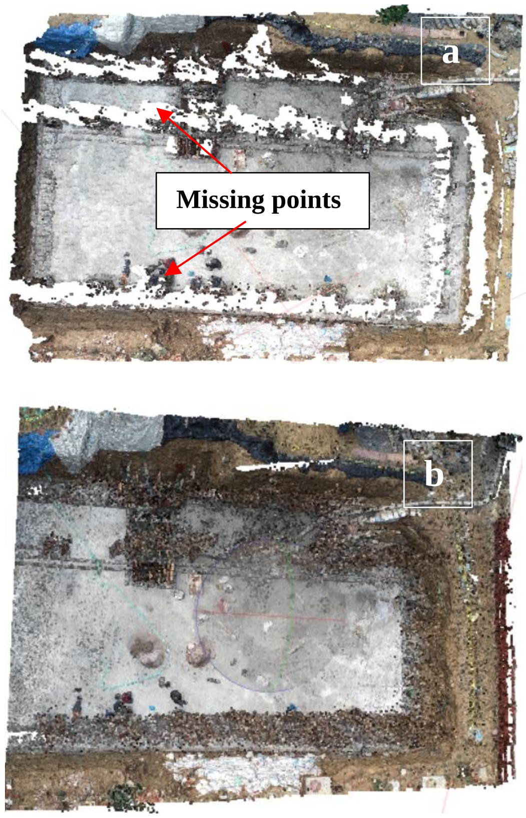

Figure 6. showing (a) missing cloud points due to occlusion (b) missing point filled up using images from modified trajectory.

4.2 Issues related to camera positioning

Aerial photographs captured using UAV can either be vertical or oblique. A vertical photograph can be taken by keeping the camera's optical axis in a direction perpendicular to the ground surface, whereas in oblique photography the camera's optical axis carries a depression angle (angle at which the optical axis is depressed below the imaginary horizontal line drawn along the camera axis) between 0° and 45° [12] [13]. Figure 7 shows a schematic representation for vertical and oblique photography.

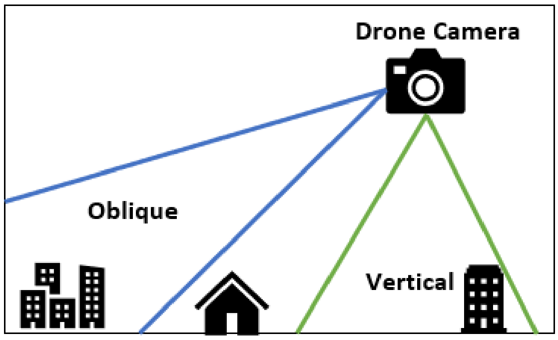

Figure 7. Representation of vertical and oblique coverage.**Solutions:** Vertical photography is beneficial in creating ortho-images that can be superimposed on the digital plan of structure for comparison. Oblique image is useful in capturing facades of structure. For vertical photography, the scale always remains a constant whereas oblique photography can have a variable coverage depending on the inclination angle of camera. If GPS or RTK option is available in UAV, images can be geotagged which eliminates scaling issues in oblique images. Rao et. al. (2018) observed 3D model reconstructed from oblique photography to be more precise and less noisy when compared to models based on vertical photogrammetry [14]. Table 1: Comparison between points generated by oblique and vertical images.

Parameters	Vertical images	Oblique images
No. of images	4	4
Processing time	49 sec	60Sec
Accuracy	Medium	Medium
No. of points	1531286	1648910

Table 1. above shows details of parameters used in capturing images using a stationary UAV to develop point cloud showing differences in data set generated due to camera positioning. Point cloud data shown in figure 8 was generated using oblique and vertical images captured using a DJI Phantom 4 Pro V2.0 with 3-axis (pitch, roll, yaw) gimbal flying at a height of 30 m.

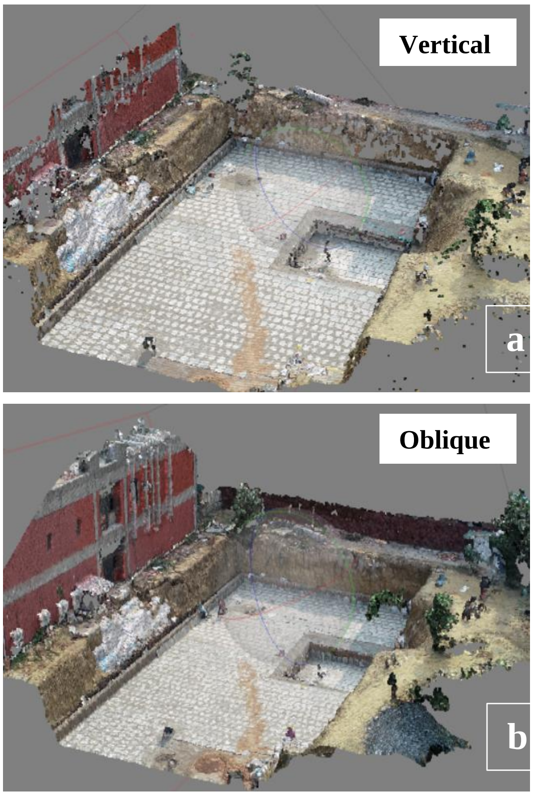

Figure 8. 3D point cloud model of the vertical and oblique images.3D point cloud model shown in Figure 8 suggest models developed using oblique images to have more coverage and feature points. The number of data points generated were also high in case of oblique images as shown in table 1. The results are in agreement with observations by previous researchers where the angle between ground and the camera was found to significantly affects the density of point cloud generated [21, 22]. Aicardi et al. (2016) and Chen et al. (2017) recommend using an inclination angle of 0º to 30º for obtaining dense data clouds as the points density start decreasing for angles above 30º.

4.3 Illumination, Reflections & Shadows

Processing reflections and shadows in photographic images poses another challenge while working with these datasets. Illumination and reflections may arise due to light scattering, textural properties of materials, or differences in site conditions. These can affect the final data at the time of processing, due to pixel value changes on similar objects leading to inaccurate point cloud generation. Shadows generated due to location of light source can also influence the accuracy of final data set.

Solutions: There are no literature available, to the best of our knowledge, towards addressing issues related to reflections and shadows in captured images. Since reflections are primarily dependent on the position of light source, use of SfM approach can be a feasible option to address this issue (figure 9 [a, b]). Selection of vertical image capturing option instead of oblique photography can also be effective in certain cases. However, the final solution is very much site dependent and the choice has to be made on a case by case manner.

However, Partama et al. (2018) suggested an alternate post processing approach to eliminate reflections and shadows, where videography was chosen over photographs, and ideal frames were extracted for processing. Since the UAV was moving continuously, the frames obtained from the video had different extrinsic properties where pixel values of objects at a given location keep changing in extracted frames. The discrepancy was adjusted using a temporal minimum filter algorithm to extract data points with smaller RGB pixel values, thereby eliminating the effect of reflection leading to an increase in RGB value [15].

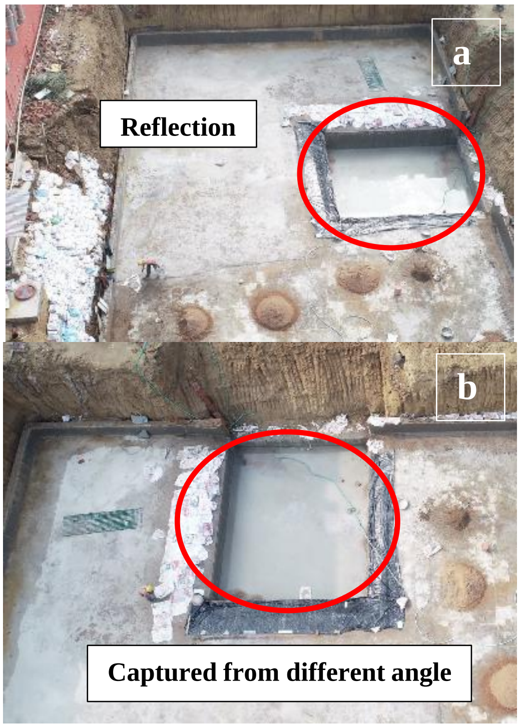

Figure 9. (a) reflection due to water (b) reflection avoided by trajectory modification

Since there are limited options available to address the issue related to shadows, two simplified approaches are generally followed during data capturing where trajectory modifications or camera positioning are altered to minimize the effect of shadows on the data set. A comparison of images collected using trajectory modification approach is included in figure 9 [a,b]. Even though selective post-processing strategies are being used to eliminate the effect of shadows, the process is time consuming and computationally heavy [16]. In summary, since the efficacy of strategies adopted to address reflection, shadows and illuminations can vary depending on site conditions, suggesting a unique solution to address the problem may not be possible.

4.4 Lightening condition:

Difference in lighting condition can arise locally due to weather conditions or due to local features restricting light availability. Wierzbicki et al. (2015) observed a 25 percent reduction in point cloud density on using data from ortho-images collected during poor weather conditions [17].

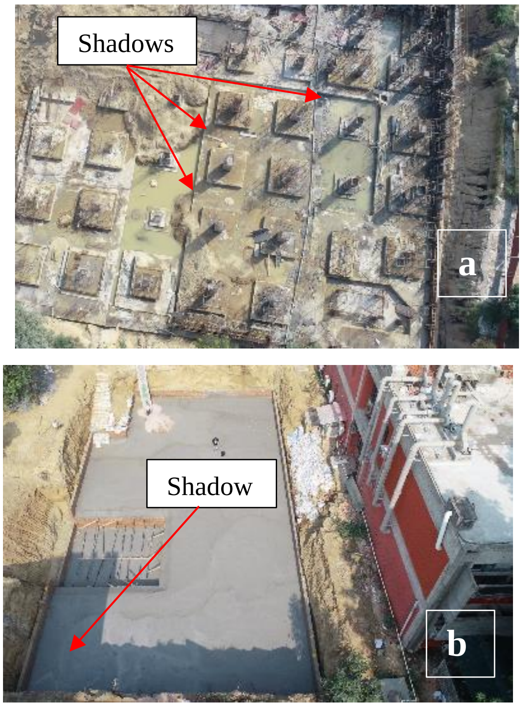

Figure 10. (a) Multiple shadows due to structural elements (b) Shadows due to adjacent structures

Since lighting issues can affect quality of the collected data, a common approach followed is to increase ISO values of photographs. This approach may not be feasible for UAVs as the proportionate increase in image capturing time can result in noise generation or motion blur due to stability issues in UAVs. Differences in lighting condition can also result in over/under exposure of images from FOV resulting in quality issues on point clouds generated.

Solutions: Even though artificial lightning can be a solution, the idea may not be feasible for all locations and often not cost effective (Perfetti et al., 2017). Efficacy of vehicle mounted lighting will also depend on power/battery/payload constraints of the UAV used. Improving quality using artificial lighting can have range limitations, as it can give a better quality image of elements in the foreground as against a noisy image for background elements. Other option is to increase ISO sensitivity and slowing down the shutter speed. ISO sensitivity represent the camera's ability of capturing light. The captured light is then converted into electrical signals, and by amplifying the signals the ISO sensitivity can be increased. Even though ISO changes allow us to capture images with many feature points, a reduced shutter speed slow down the data collection process (due to the additional time taken by cameras to adjust to the changes). Increase ISO can also lead to noise, grains, and blur which also get amplified with the signals. Method of changing ISO may not always be beneficial while aligning images for processing as the available feature points vary significantly with luminosity factor due to differences in captured pixel properties [18]. Use of High Dynamic Range (HDR) techniques can result in motion blur due to the longer exposure time required for capturing images. Hence the option may work reasonably only in cases were vehicle movements can be controlled manually.

4.5 Textural data

Properties of pixels in raster image captured from UAVs is dependent on texture of the object. Processing images of objects with quasi-uniform color, say concrete, is often challenging as distinctive feature point are hard to obtain. Hence feature points are often identified along edges and corner of the element which has different pixel values from the rest of the surface. The mesh generation and reconstruction from these data are often less accurate due to decrease in point cloud density.

Figure 11. 3D point cloud model of the under-construction foundation work.

Solutions: During field experiments, the authors came across issues due to reduced point density while performing dense reconstruction of objects with poor texture properties. Textural issues were also found to be dependent on lighting conditions as the quality of images reduces with deterioration in lighting as observed in point cloud data given in figure 11.

4.6 Blind Spots

Accessibility issues can create problems during data collection. Data collection on open construction sites like pavements are easier in comparison with data collection on complex residential structure due to accessibility issues. The field of view (FOV) for UAV is limited and typically lies between 70° to 95° [19]. The coverage of an area also depends on the inclination angle of camera used during data collection. Figure 12 shows an example of a blind spot encountered by the author during field study.

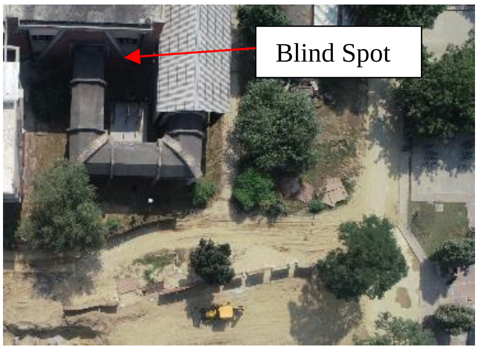

Figure 12. Blind spot encountered during the field experiment.

Solutions Perfetti et al. (2017) suggested the use of wide angle lenses such as fisheye to enhance the FOV during data accusation [18]. However, the level of details achievable using this approach is often less than what is required for generating a dense point cloud. Use of vertical camera positioning instead of oblique positioning may help getting more feature points than by using a wide-angle lens.

5 Post-processing issues

5.1 Blurred Images

Since UAVs fly at a height of more than 30m to capture images, the captured data is often affected by wind, vibration and stability issues of UAV. In Blurred images, pixels get distorted; the RGB values and vectors of the image changes, which can all affect the quality of point cloud generated.

Solutions: Haar algorithm (HAAR), intentional blurring pixel difference algorithm (IBD), SIEDS (saturation image edge difference standard-deviation) are some of the available techniques to detect and remove blur from the images. Nobert et al. (2011) evaluated the effectiveness of SIEDS algorithm on two data sets collected using UAV and found the algorithm to be reliable in detecting blurred images [20][21].

5.2 Coordinate errors

Modern UAVs often have on board GPS that can create geotagged images and thereby generate geo tagged cloud points. However, problems can arise due to differences in latitude or longitude data for a given location in the dataset collected during multiple runs as the GPS may link with different set of satellites during individual runs.

Solutions: Use of real-time kinematics (RTK) in post-processing of data or use of local coordinate system instead of the global coordinate system can help overcome this issue [20].

6 Conclusion

Construction sites pose several challenges during collection and photogrammetric processing of images collected using UAVs. Use of occlusion-aware control mechanism developed by Semsch E. et al. (2009) may be an effective option for flight planning operations. Issues related to static and dynamic occlusions during data collection can be addressed in part by changing trajectory and angle of capturing data or by using machine learning approaches during post processing to remove irrelevant data points. Cloud density was observed to be higher when oblique images were used in point cloud generation when compared to vertical images. Even though density of point cloud may be compromised, mesh generation and reconstruction using edge and corner based feature points appears to be the only available option to segregate objects with similar textural properties. Discrepancies arising from differences in GPS coordinates may be addressed either by using RTK or a local coordinates system.

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