Visualization of as-built progress data using construction site photographs: two case studies

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Abstract

The collection of as-built data for construction progress monitoring remains challenging. This paper develops two case studies on image-based modeling, in which point cloud models are created based on the photo collection of the construction site. The first case considers 399 unordered construction images previously taken for purposes other than progress monitoring, whereas the second case considers 118 photos that have been taken based on the results of the first case study. The results of the first case study are employed to improve the quality of the point cloud model in the second case, using the site photo collection captured by the first author for the purpose of establishing an enhanced point cloud model. The results of the two case studies are compared. Furthermore, the results are compared with those of other researchers and found that they are in a good agreement with other reported results. Finally, some suggestions are proposed to improve the image-based model for construction progress monitoring, particularly for industrial projects that involve a large construction site and various work packages.

Keyword

Construction site photographs, Image-based modelling, Visualization, Progress monitoring, Decision making, Information technology; Huge construction sites

1 Introduction

Decision making during the construction phase significantly depends on accessible as-built and as-planned information. Daily construction site photographs are robust sources of as-built data that can be easily captured by either the construction manager or any site staff member. A 3D image-based model can also be automatically created daily using computer vision algorithm and image-processing techniques. Such models can aid in the visualization of discrepancies between as-built and as-planned data in an augmented reality environment, which facilitates progress monitoring. A project manager's effective decision making in selecting corrective actions during the construction phase significantly depends on the immediate detection of schedule delay, and such corrective actions can prevent delays and budget deficiencies [1]. Figure 1 shows that the project control process mainly occurs during the construction phase. This process comprises three steps, namely, monitoring, comparing, and corrective action selection. In the first and second steps, members of the project management team prepare information products that visualize important data to facilitate decision making by the project manager. Figure 1 also shows various graphs (e.g., gaunt charts or s-curves) and images that can be used to present the status of the construction process. From it, we can thus determine whether such material can help the project manager to immediately identify discrepancies between actual and as-planned performance.

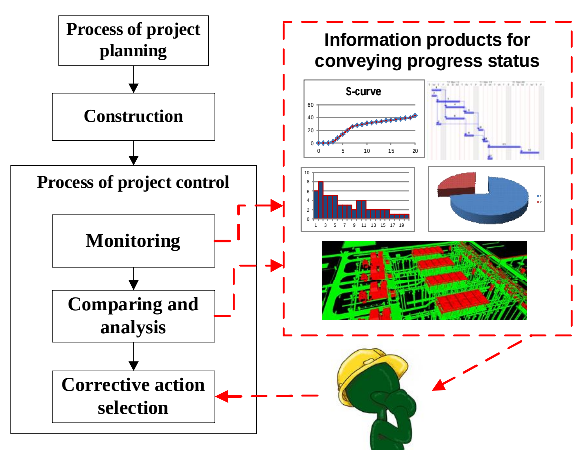

Figure 1. Using information products for decision making

Several researchers highlighted the limitations of current manual data collection approaches in terms of speed and accuracy. According to Akinci et al. (2006), field staffs in construction sites spend 30% to 50% of their time recording and analysing field data [2]. Moreover, data transfer from a site to a field office requires additional time, because most data items are not captured digitally [2]. Daily construction site photographs, which are robust sources of as-built data for construction progress monitoring, comprise a usable and easily accessible source of information for as-built progress data [1]. Digital images can be easily captured without additional cost for construction projects [3]. According to Section 4.21-b of the FIDIC series book (Red Book)—Conditions of Contract for Construction, photographs are among the progress reporting requirements that a contractor should regularly (e.g., monthly) send to the owner [4]. Aside from progress documents, photographs have more applications, and can be easily captured using a handheld digital camera by a contractor staff, construction manager, superintendent, the owner's representative, the subcontractor, or other project team members. In this approach, collections of photographs are used to reconstruct the 3D as-built scenes using computer vision algorithm and image processing techniques [1], [3].

This paper focuses on the creation of 3D as-built point cloud models using construction site photographs. By registering these 3D models on a 4D as-planned model, the progress of construction projects can be visualized in an image.

2 Background

In 2006, augmented reality was proposed as a technique for the visualization of construction progress monitoring [5]. The use of augmented reality enables the visualization of construction progress in an image by superimposing a 3D model on the actual construction scene, and then highlighting discrepancies from the schedule by color coding any part of a structure. Golparvar-Fard et al. (2009) then proposed a visualization system called 4D Augmented Reality (D^{4}AR) for the automatic visualization of construction progress monitoring [1]. In this system, daily site photographs are captured using a digital handheld camera by anyone involved in a construction project [1]. In D^{4}AR, the location of a photographer and the orientation of each camera are computed based on the images using computer vision algorithm and image processing techniques. The generated 3D image-based model is then used as an overlay on the 4D as-planned model for the visualization of progress monitoring; here, color coding makes it easier for the user to understand what the model represented [1]. Finally, Golparvar-Fard et al. (2011) reported that the identification, processing, and communication of progress discrepancies are enhanced by the integration of the visualization of as-built and as-planned performance and can thus serve as a powerful remote project management tool for remote decision making in the A/E/C and FM industries [3].

3 Computer vision techniques for image-based modeling (IBM)

Several computer vision techniques for IBM have recently been used to create 3D models from a collection of input images (i.e., unordered daily construction site photographs in our study). In this approach, the locations of the photographer who captures the images are unidentified, and images are captured under various illumination, resolution, zoom, and quality conditions [6], [7], [8]. Then, correspondences between images should be estimated for scene reconstruction from an image collection. The goal of correspondence estimation relative to construction progress monitoring or to any use of the image collection is to take a raw set of images and then identify sets of matching 2D pixels across all the images [6]. Each set of matching pixels represents a single point in 3D [7]. For correspondence estimation, the distinctive local features of each image are initially identified, after which similar-looking features in different images are determined [6], [7]. Once the correspondence problem is solved, the structure from motion (SfM) procedure is used to estimate the location of the camera and 3D points [1], [6], [7], [8]. The SfM procedure studies both structure (i.e., 3D view of the construction site) and motion (i.e., motion of the camera within the construction scene) [6]. SfM estimates the extrinsic and intrinsic parameters of a single image pair [8]. Thus, the process must start with an ideal initial image pair with good estimates of camera parameters for the chosen pair [1], [8]. In the current paper, the initial image pair is selected manually. In our case study, the sparse model becomes vague and difficult to understand when the inappropriate image pair is selected. To estimate the intrinsic parameters of a camera, the focal length must be extracted from the exchangeable image file format (EXIF) tags of JPEG images to initialize the focal length of the new camera [6], [8]. In this paper, the sizes of original images are changed using Xnview [9] software to maintain the EXIF tags. All computer vision techniques are applied using VisualSfM software [10],[11]. We use the SIFT of Lowe [12] for feature detection as well as the functions available in

VisualSfM [10],[11] for matching and SfM. The process of capturing images and as-built point cloud model are shown schematically in Figure 2.

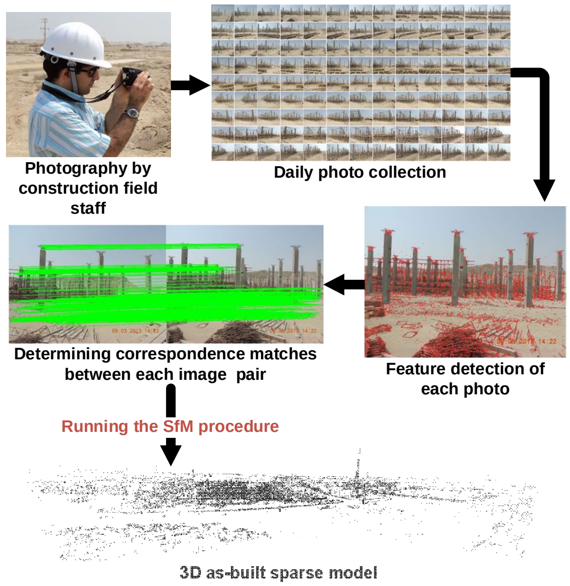

Figure 2. Process of collecting as-built data resulting in the reconstructed 3D as-built point cloud model

4 Case study

Two case studies are implemented. The first uses an unordered photo collection previously captured for purposes other than progress monitoring and image-based modeling.

The photographs in this collection are captured randomly from any part of the construction site for documentation and for presentation in weekly and monthly progress reports. Some of these photographs are unrelated to project management tasks or are captured under poor conditions. For instance, some are taken from afar, or with the glare of the sun. More importantly, some are captured without any overlay, which is needed for good image-based modeling.

The second study uses the results of the first study and the images captured by the first author for the purpose of progress monitoring. This case study is conducted to investigate the quality of the point cloud model, with the aim of using the results for enhanced image capture and, consequently, improved IBM. In this section, a collection of images for a recent project is used to establish an as-built point cloud model of the construction scene. In this case, the photographs captured the scenes related to project management tasks only. Moreover, the photographer tried to capture photographs with a good overlay to achieve proper image-based modeling. Figure 3 shows the development of the models for these studies.

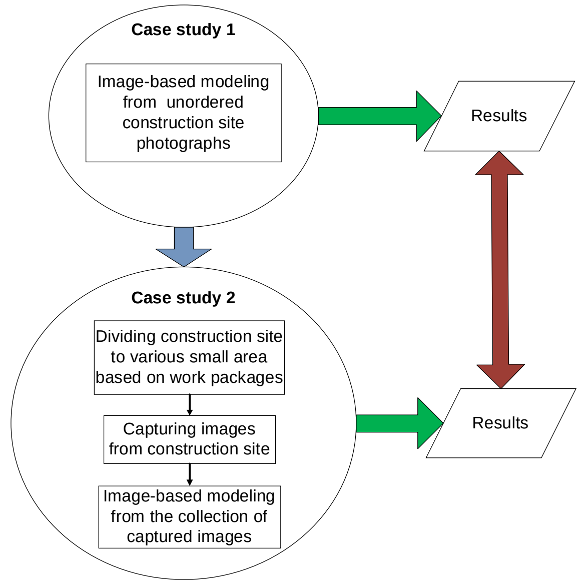

Figure 3. Development of the models for the two case studies

4.1 Case study 1

The project is the construction of a gas compressor station. The construction site covers approximately 20 ha, and the image collection includes approximately 3000 photos. A cutoff date is chosen, and images captured after this date are eliminated, resulting in a final number of 399 remaining images. These images were captured with different resolutions and under different illumination conditions. Furthermore, different staff members captured these images using different digital cameras.

Many of the images in the collection are not relevant to project management tasks. Moreover, the photographer was not able to choose the appropriate frame to capture the photographs of the scenes related to project management tasks. Figures 4 and 5 show examples of faulty photography. Figure 4 shows an image with the minimum number of SIFT features in the collection, with the location visualized by red points. This photograph is captured far from the structure and under the glare of the sun, which caused a significant decrease in the number of SIFT features. Figure 5 shows an image sample with an inappropriate frame of photography. This image has the maximum number of SIFT features in the collection, but many of these features (which can be seen on the ground) are not used for image-based modeling for the purpose of project progress monitoring.

Figure 4. The image in the collection with minimum number of SIFT features location visualized by red points

Figure 5. The image with maximum number of SIFT features location visualized by red points

This paper uses VisualSfM software [10], [11] to solve the correspondence problem and bundle adjustment for the 3D sparse modeling of a construction scene. The first step is feature detection, which is implemented using the SIFT algorithm [12]. Figure 6 shows the number of SIFT features determined by the SIFT detector [12] for each image. As can be seen, the tolerance between the maximum and minimum numbers of features is 15783. The average number of detected SIFT features is 5904. Table 1 shows the maximum and minimum values of SIFT features. These values and the domain between them show that the scenes chosen by different photographers are vastly different, disproportional, and lack rational dependency.

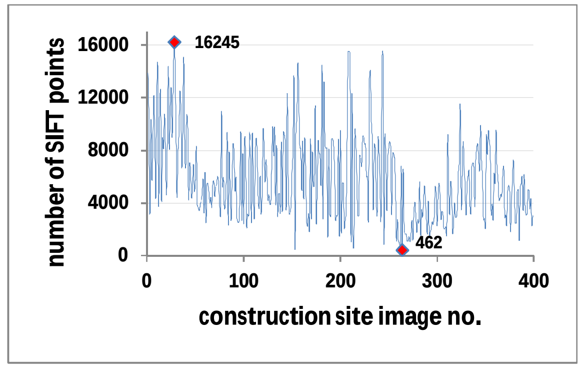

Figure 6. Number of SIFT features in 399 images of various sizes

Table 1. Maximum and minimum numbers of SIFT features in the image collection (case study1)

Image no.	No. of SIFT features
28	462 (min)
264	16245 (max)

The images and their feature matrix are then imported to VisualSfM [10],[11], which computes for the missing matches. Figure 7 shows one image pair from the collection with the correspondence matches which are shown by solid lines.

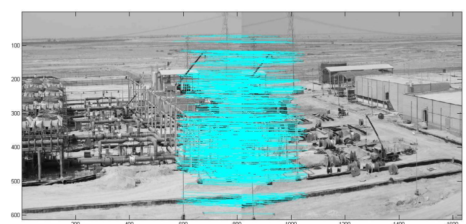

Figure 7. Pair of images with 831 matches

Finally, the appropriate initial image pair is manually selected, after which the 3D reconstruction of the construction scene is established by running the SfM procedure. The reconstructed sparse scene with the estimated camera location is shown in Figure 8.

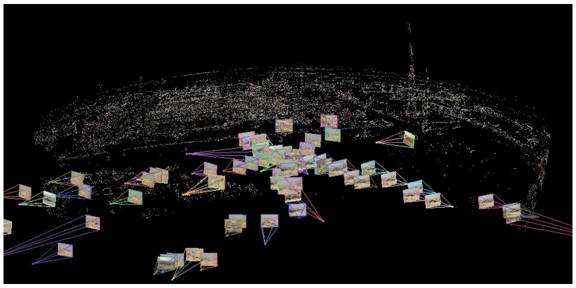

Figure 8. Sparse 3D model reconstructed from 99 images with camera frusta

The reconstructed scene, shown in the Figure 9, has relative coordination, such that the absolute coordinates of these points can be measured using SfM_Georef v.2.3 [13] by defining coordination points (X,Y,Z) for at least three points. This transformed model is then overlaid on the station plan shown in Figure 10. According to Figure 10, the reconstructed scene covers only a small area of the sites, although the photo collection includes a scene representing the entire construction site. The recall characteristic (portion of the number of images used to number of all images) for this photo collection is 0.25, a value that is lower than that obtained by previous studies conducted by Golparvar-Fard et al. (2011) [3]. The low quality of this 3D sparse model can be attributed to the small number of images relative to the large area of the construction site (20 hectares) for the gas compressor station. In addition, failure to overlay the images properly hinders the establishment of a good image-based model. Figure 4 and Figure 5 show that some images have been captured in poor conditions (e.g., with the glare of the sun) or from a far distance or with a poor selection of frame, resulting in a small number of SIFT features or a huge amount that is not relevant to the project management scope. As a result, few correspondence matches are obtained, thus leading to a low-quality 3D sparse model.

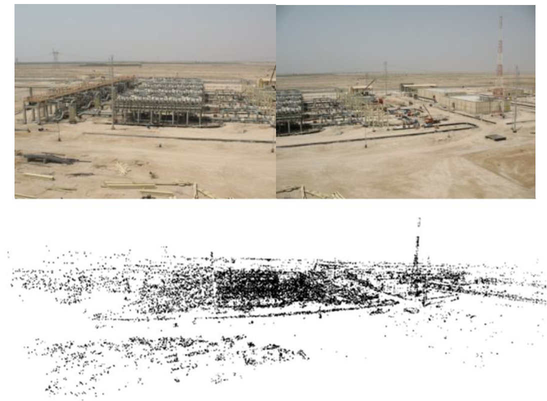

Figure 9. Two images from the photo collection (Up)- point cloud model (down)

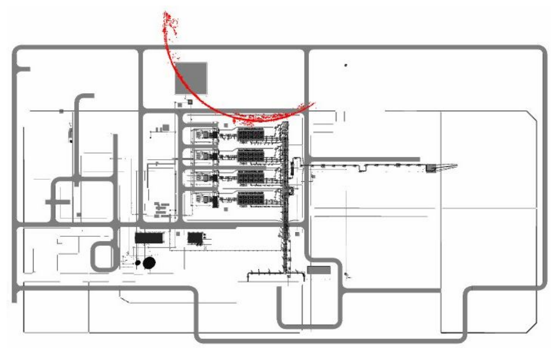

Figure 10. Plan of the gas compressor station overlaid by 375,273 reconstructed points

4.2 Case study 2

After performing Case 1 and confirming the low quality of the 3D point cloud model (recall=0.25), the construction site used for other project is the same as that used in Case 1 is divided into a large number of small areas. For example, industrial projects, such as gas compressor stations, involve various building and work packages (e.g., buildings, piping area and air coolers). In Case 2, we focus on one of the buildings (control building) with the size of 17 m x 40. A total of 118 photographs are captured in 6 min, and the conditions under which these images have been captured are shown in Table 2. These images have been captured for IBM with the aim of a proper overlay between images, which is in contrast to the randomly captured Case 1 images. According to McCoy et al. (2012), the images were captured approximately 9 m from the building to obtain good results for IBM [14].

Figure 11 shows the number of SIFT features for all 118 photos. According to Figure 11, the tolerance between the maximum and minimum numbers of features is 10752 which is less than the tolerance between the maximum and minimum numbers of SIFT features in the Case 1. This condition indicates that the method used to capture the scenes is the key factor for creating an enhanced point cloud model. If we use a larger number of photographs in Case 1, an improved model can be obtained, and recall can be increased. However, the process time required to identify features and solve the correspondence problem is increased. The average number of detected SIFT features is 12457, considerably higher than the average number in the Case 1. This finding indicates that in Case 2, we have more features on average, such that we expect to have increased correspondence among all photos in the collection and, ultimately, an improved point cloud model. The values listed in Table 3 show the maximum and minimum numbers of SIFT features. Figure 12, 13 show these images with the visualized SIFT feature location.

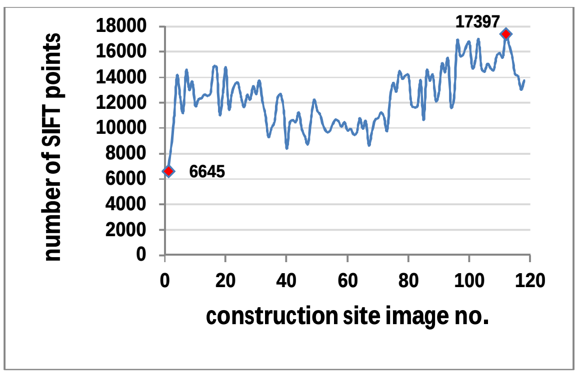

Figure 11. Number of SIFT features on 118 images a size of 1613 x 1210. Images are reduced to 35% of the original.

Table 2. Characteristics of the captured images

Photography Characteristic	
Camera model	Nikon Coolpix P510
Number of captured photos	118
Image resolution(pixel)	4608 x 3456
Photography duration	6 minutes
Lighting condition	Sunny

Table 3. Maximum and minimum numbers of SIFT features in the image collection (Case study 2)

Image no.	No. of SIFT features
1	6645 (min)
264	17397 (max)

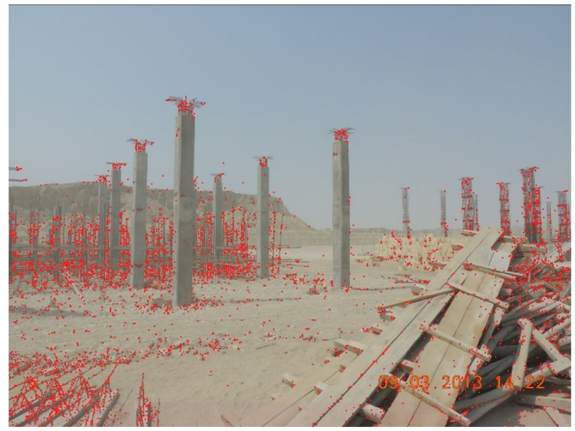

Figure 12. The image in the collection with minimum number of SIFT features location visualized by red points

Figure 13. The image in the collection with maximum number of SIFT features location visualized by red points

Figure 14 shows the reconstructed point cloud model with a reconstructed camera denoted by 100 frusta. Figure 15 shows the 3D sparse model in dense form, as determined by the CMVS/PMVS module in VisualSfM software [10],[11].

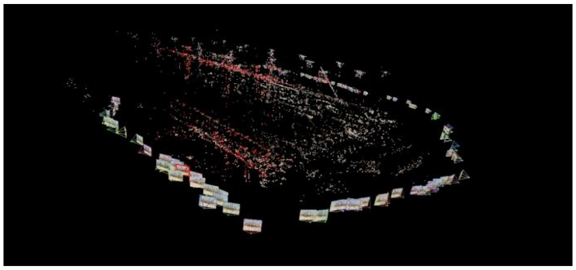

Figure 14. Point cloud model reconstructed from 100 images with camera frusta

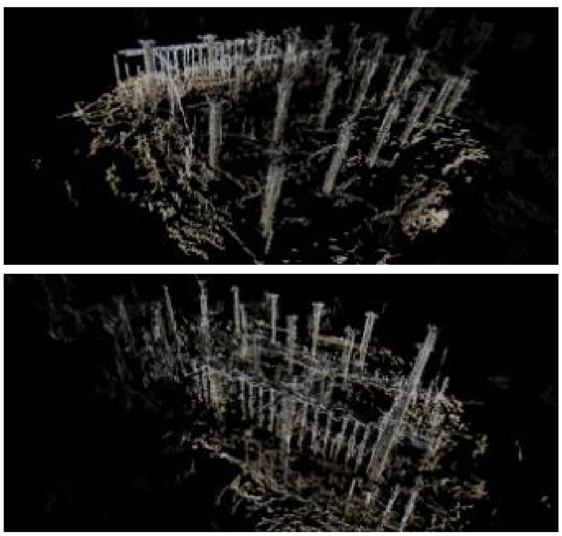

Figure 15. 3D model reconstructed from 100 images

5 Conclusion

As-built progress data collection is among the most challenging tasks in progress monitoring. However, daily construction site photographs can be used as a robust source of as-built progress data. This paper develops two case studies, and an as-built point cloud model is created for both cases. The results of the first study are used to improve the second case. The results of the 3D point cloud model in both cases are then compared, from which we have drawn several conclusions.

First, a group of images in good condition and with proper overlaying taken from only one view of the site or a group of images sporadically taken from various parts of the construction sites without proper overlaying or with faults during capturing. Such faults include the glare of the sun or capturing a scene that is unrelated to the project management task can be used to reconstruct only a small area of a large construction site. Therefore, the sparse reconstructed model which is resulted from Case study 1 uses only 25% of the images (Recall=0.25). The model can show only a particular view despite the existence of images taken from another view. Therefore, Case 1 (Recall=0.25) exhibited lower recall than Case 2 (Recall=0.85).

Second, in such a large industrial project (site area is approximately 20 ha), some parts of the site in which photographs are captured should be divided into smaller parts so that images can be captured more accurately. For example, every building or piping area must be considered separately. Therefore, the site is divided into small areas in Case 2. In these areas, photographs are taken from one of the buildings included in the project considered in Case 1. The recall characteristic in the Case 2 is 0.85, a value that is in a good agreement with other reported results obtained by previous studies conducted by Golparvar-Fard et al. (2011) [3].

Table 4 summarizes the results. The results are benchmarked on a computer with 2.4 GHz Intel® Core i5 CPU, 2.00 GB of RAM, and a Windows 64-bit platform. According to the results shown in Table 4, changing the strategy of capturing construction site photographs in case 2 increases the recall considerably. The average number of detected features in case 2 also increases considerably. Although the collection of images in both cases are not similar and are from two different projects, the higher number of features means that the proper image based model we expect that the results show this expectation.

Table 4 Experimental data

	Case study 1	Case study 2
Total # of images	399	118
# of used	99	100
# of points recovered	375,273	74,938
Recall(#of used/Total)	0.25	0.85
Average number of detected features	5904	12457
Computation time	375 min	210 min

Finally, the authors do not refute the capability of the computer vision algorithm to establish 3D point cloud models for visualizing as-built progress data from unordered construction site photographs. However, we need to capture numerous photographs, all with good overlaying, when using this method. This condition is impossible for huge construction sites. Even if such goal is possible, computation time will be extended by up to more than a day, in some cases. Therefore, the authors strongly suggest the division of huge construction sites to smaller parts. Then, 3D point cloud models can be constructed and visualized separately for every working package.

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