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CROWD-SOURCED VISUAL DATA COLLECTION FOR MONITORING INDOOR CONSTRUCTION IN 3D

FOUAD AMER and MANI GOLPARVAR-FARD

Dept of Civil & Environmental Engineering, University of Illinois at Urbana Champaign, Urbana, United States

Complete and accurate 3D monitoring of indoor construction progress using visual data is challenging. It requires (a) capturing a large number of overlapping images, which is time-consuming and labor-intensive to collect, and (b) processing using Structure from Motion (SfM) algorithms, which can be computationally expensive. To address these inefficiencies, this paper proposes a hybrid SfM-SLAM 3D reconstruction algorithm along with a decentralized data collection workflow to map indoor construction work locations in 3D and any desired frequency. The hybrid 3D reconstruction method is composed of a pipeline of Structure from Motion (SfM) coupled with Multi-View Stereo (MVS) to generate 3D point clouds and a SLAM (Simultaneous Localization and Mapping) algorithm to register the separately formed models together. Our SfM and SLAM pipelines are built on binary Oriented FAST and Rotated BRIEF (ORB) descriptors to tightly couple these two seperate reconstruction workflows and enable fast computation. To elaborate the data capture workflow and validate the proposed method, a case study was conducted on a real-world construction site. Compared to state-of-the-art methods, our preliminary results show a decrease in both registration error and processing time, demonstrating the potential of using daily images captured by different trades coupled with weekly walkthrough videos captured by a field engineer for complete 3D visual monitoring of indoor construction operations.

Keywords: Production control, Data collection decentralization, Automation, Computer vision, Virtual construction, Structure-from-motion, Simultaneous localization and mapping.

1 INTRODUCTION

Today, capturing images and videos on construction sites using smartphones and drones has become an indispensable part of the daily workflows conducted by the field engineers and trades (Han and Golparvar-Fard 2017). The large volume of visual data has enabled 3D reconstruction techniques to be built on Structure-from-Motion (SfM) and Multi-View Stereo (MVS) algorithms and record exterior construction activities in high details and at any desired frequency (Golparvar-Fard *et al.* 2009, 2011). However, producing complete 3D as-built models for indoor construction, considering limited visibilities and fields of view of cameras, requires a large set of overlapping images and necessitates that connecting areas such as hallways and corridors be included in captured images (Kopsida *et al.* 2015). Such areas are usually textureless and colorless, and they have low lighting conditions causing SfM based reconstruction algorithms to often fail in producing compelling 3D models. Acquiring large sets of overlapping images by a single person on the jobsite -particularly in hallways and entrances where field of view of a camera is limited- can also be very time-consuming.

The opportunity is the following: indoor construction activities are mostly performed by different teams working in dispersed locations, and each team is interested in recording their own activities as proof of timely completion of their tasks or for liability purposes. We built on this *decentralized* and *crowd-sourced* data capture opportunity, and we propose a new hybrid 3D reconstruction method that (a) maps indoor construction work locations in 3D and at any desired frequency and also (b) supports routine daily reporting of activities. The proposed method uses a pipeline of SfM to register local images taken by the trades in 3D and feeds them into MVS dense reconstruction algorithm to produce dense 3D point clouds for each work area. Videos taken during weekly walkthroughs from the entirety of the site and particularly hallways and corridors are then fed into a monocular SLAM to connect the locally produced dense 3D point clouds. This approach enables project stakeholders to use their daily field reporting images and create dense 3D models of each work location at a high frequency (e.g., daily) while only needing a video walkthrough of the entire workspace to be captured on a low frequency (e.g., weekly) to link local reconstructions together. In the following, we first review the related work and present the proposed reconstructed method. Next, we present the experimental results from conducting a pilot on a real-world project. Finally, we discuss the perceived benefits and challenges of the proposed method for scaling across all project sites.

2 RELATED WORK

In the past decade, image and video-based 3D reconstruction has been the center of a large number of studies. Some of these methods use unordered site photographs together with SfM based workflows to create dense 3D point clouds (Trupp *et al.* 2004, Quiñones-Rozo *et al.* 2008, Dai and Lu 2008, Golparvar-Fard *et al.* 2009, and Golparvar-Fard *et al.* 2012). Others focus on increasing registration and 3D reconstruction accuracy and completeness by using ground control points and visual markers (Tuttas *et al.* 2014 and Karsch *et al.* 2014). The use of stereo cameras and videogrammetry along with a knowledge of *a priori* geometry to create accurate 3D as-builts for infrastructure sites has also been investigated by Fathi and Brilakis (2011), Brilakis *et al.* (2011), and Rashidi *et al.* (2015). As a result, commercial solutions such as Pix4D, Reconstruct, Autodesk RECAP, and Bentley Context Capture are now heavily used to produce highly detailed 3D as-built models of construction sites in outdoor environments. However, mapping texture-less 3D indoor environments on construction sites using images is still an open research challenge, and many solution providers encourage practitioners to use laser scanning or RGBD devices (e.g., Matterport) to conduct visual data capture in their indoor environments. While these technologies are appealing, yet they are prohibitively expensive for daily use across all construction projects.

Regardless of being captured and produced for indoors or outdoor environments, as-built 3D point clouds should be registered together and/or with BIM for any performance tracking or quality control purposes. Point-based registrations based on manually matching a set of points in both scans (Akinci *et al.* 2006, Golparvar-Fard *et al.* 2009), target-based registrations using tie points introduced to the site (Bosché *et al.* 2009), and feature-based registrations based on automatically extracting and matching distinguishable scene features (Bosché 2012) have been proposed. Furthermore, using Iterative Closest Point (ICP) (Golparvar-Fard *et al.* 2009, Bosché 2010, and Turkan *et al.* 2014) and Principal Component Analysis (PCA) refined by ICP (Kim *et al.* 2013) were investigated to improve registration accuracies and automate the process. Despite these efforts, a complete automated and feature-based registration process to tie scattered local point clouds is still needed, which is the focus of the current study.

The joint application of BIM and point clouds for automated progress tracking has also been a topic of several recent research studies. El-Omari and Moselhi (2008, 2011), Bosché (2010), Golparvar-Fard *et al.* (2012), Turkan *et al.* (2014), Tuttas *et al.* (2014), Lin and Golparvar-Fard (2016), Han *et al.* (2017), and Son *et al.* (2017) are all examples of relevant works, however, tailoring their use for indoor construction tracking is still under-investigated, and current solutions are not designed to overcome the additional complexities of mapping indoor environments. Frameworks on automatically identifying construction components in images (Roh *et al.* 2011) or assessing the state of indoor partitions (Hamledari *et al.* 2017) are also proposed but the location and orientation of the indoor images with respect to BIM is assumed to be known as a priori.

Kopsida *et al.* (2015), Hamlederi and McCabe (2016) and Han and Golparvar-Fard (2017) have specifically revealed that lack of texture, highly varying lighting conditions, the nature of indoor construction operations where progress is mostly associated with changes in wall surfaces, and the need for acquiring a large number of overlapping images can all make the process of acquiring indoor images by a single party and processing them be inefficient, time consuming, and in most extreme cases very difficult to implement. To address these inefficiencies and challenges, we propose a method that allows for crowd-sourcing the data collection process by enabling the automatic fusion of different partial 3D reconstructions at any desired frequency.

3 PROPOSED METHOD

We propose a hybrid SfM-SLAM 3D reconstruction algorithm along with a decentralized data collection workflow to map indoor construction work locations in 3D and at any desired frequency. This method builds on (Amer and Golparvar-Fard, 2018) and uses SfM and MVS algorithms --developed on (Gargallo 2016)'s OpenSfM-- to create dense 3D reconstructions from images gathered by different trades at their specific work locations on a daily basis. These point clouds are tied together via a feature based SLAM algorithm using walkthrough videos taken at a lower frequency (e.g. weekly or bi-weekly). The proposed SLAM procedure is built on ORB-SLAM2 (Mur-Artal and Tardos, 2017) and both SfM and SLAM reconstructions are performed using binary ORB features. This strategy, as demonstrated below, allows us to tackle the problem of large datasets required to map indoor construction areas by creating dense reconstructions only in the areas where they are needed. It also avoids the long computation time of the offline SfM method on large datasets and instead assigns the task of mapping connection areas such as hallways and corridors to the SLAM procedure.

To deploy the proposed method in practice, we propose a workflow which consists of the following Three phases: Planning, Monitoring, and Control. The planning phase aims at identifying the activities anticipated for the following week or two, their locations, and their assigned crews/trades. It takes place in weekly or bi-weekly meetings and it is based on 4D BIM and/or Weekly Work Plans (WWPs).

The monitoring phase consists of (1) data collection and (2) data processing. Data collection is distributed among different crews/trades, and it is composed of capturing a video of all anticipated work locations by a single person (e.g. field engineer) at a low frequency (e.g. weekly) and collecting different sets of local images of specific work locations by their respective crews/trades at any desired frequency (e.g. daily). After the data is collected, the video is used to create a sparse point cloud of the entire site (local work locations and connecting areas) using the SLAM thread of the proposed algorithm, and the local sets of images are used to create local dense point clouds of every work location separately using the SfM + MVS thread of the algorithm. The local point clouds are then registered with the global point cloud by finding matching points using a hamming distance nearest neighbor search and then calculating a rigid 3D transformation using a Random Sample Consensus (RANSAC) loop. The RANSAC loop ensures the calculated transformation is geometrically consistent with a significant number of the matches. Finally, the control phase starts by registering the locally-dense as-built map with BIM which also localizes all the collected images and video frames with respect to BIM. This registration can be done manually or using surveyed visual tags. The resulting alignment would allow different 2D image-based and 3D point-cloud based progress assessment methods to be implemented on top of the proposed algorithm.

4 CASE STUDY AND PRELIMINARY RESULTS

The proposed method was tested on a real-world project. The test aimed at mapping the work done in two different and scattered locations (L1 and L2) and registering them together and within BIM. A walkthrough video of the jobsite was captured and was later processed to create a sparse 3D reconstruction of the entire jobsite (L1, L2, and the connecting areas). Additionally, two different sets of images of both work locations were gathered separately and were later processed to create dense reconstructions of both local work locations (L1 and L2) (Figures 1d and 1e). The created local maps were then registered with the global point cloud automatically using ORB feature matching which results in the reconstruction of a locally dense point cloud of the entire site (Figures 1a and 1b). The resulting point cloud is then manually registered with BIM using identifiable common points (Figure 1c). The registration accuracies are illustrated in Table 1, and the performance of the ORB-based SfM and MVS pipeline is illustrated in Table 2.

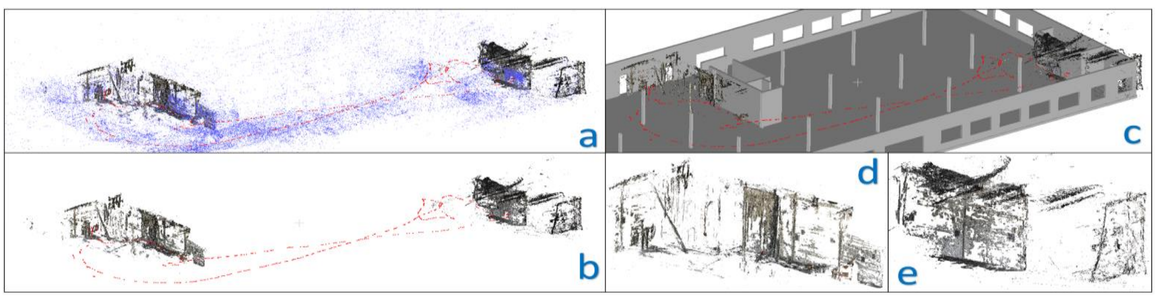

Figure 1. Dense local point clouds aligned with the sparse point cloud and with BIM. The red dots (in b and c) show the trajectory of the walkthrough video.

Table 1. Registration accuracies.

Point Clouds	Registration Error (cm)
L1 to site map	**3.97**
L2 to site map	**2.58**
BIM to site map	31.84

Table 2. Performance of SfM and MVS using ORB.

Location	Number of Images	Images Overlap	Number of Successfully Registered Images	Sparse Reconstruction (SfM) Density	Dense Reconstruction (SfM+MVS) Density	Sparse Reconstruction time	Dense Reconstruction time	Total Reconstruction Time
L1	63	60-80%	33	11,255	359,260	19 min	22 s	~20 min
L2	42	60-80%	15	1,159	242,712	10 min	6 s	~10 min

Compared to (Amer and Golparvar-Fard 2018), where the local point clouds were reconstructed using HaHoG features (Hessian Affine Histograms of Oriented Gradients) and the registration was performed using visual tags, we notice that the number of registered images has decreased from 60 to 33 for L1 and from 41 to 15 for L2 also leading to a decrease in the densities of the generated local point clouds. However, the registration accuracy increased from an average of 7.7 cm (+ an ambiguity of 36.3 cm due to the use of tags) to an average of 3.28 cm (the average of the registration of both local point clouds in Table 1). The computation time for reconstruction also decreased from ~22 min to ~15 min.

5 CONCLUSIONS

We presented a new method to map indoor construction areas in 3D using a crowd-sourcing approach to visual data capture. The proposed method uses binary ORB features to reconstruct detailed local point clouds of scattered work locations and to reconstruct a sparse global point cloud of the entire site. The same binary features are then used to tie the different local clouds together and to create a 3D reconstruction that is only dense in work areas where construction activities need to be mapped. The experimental results revealed shorter processing times and higher registration accuracies compared to state of the art algorithms. Future work will focus on implementing a mobile version of this hybrid SfM-SLAM algorithm to provide feedback to the field engineer on the completeness of capture and on applying automated point-cloud based and image-based reasoning systems for indoor construction progress tracking purposes.

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