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TOWARDS REAL-TIME SCAN-VERSUS-BIM : METHODS APPLICATIONS AND CHALLENGES

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ABSTRACT

There has been much work on Scan-vs-BIM, and it has implications on construction productivity, quality, and safety. However, these methods need to be extended /altered to do real-time Scan-vs-BIM. This paper presents the extensions for existing methods such as registration, point matching, object detection, and pose estimation to cater to real-time Scan-vs-BIM. Further, we describe the applications for such methods in construction and describes the challenges for their implementation. We conclude by implication of this paper on researchers working on augmented reality and construction robotics.

INTRODUCTION

The construction sector is going through a paradigm shift during the current pandemic by accelerating the adoption of several digital technologies (Ogunnusi et al., 2020). It has become ever more critical to reduce the number of people on the construction site and automate workflows to reduce workforces. Although pandemic can be treated as a catalyst, the construction sector embracing digital technologies such as Building Information Modelling (BIM) (Sacks, Girolami and Brilakis, 2020), construction robotics (Melenbrink, Werfel and Menges, 2020), and augmented reality (Ahmed, 2019). These technologies, along with the advancement in real-time Scan-vs-BIM technology, provide opportunities for a connected construction site, resulting in increased productivity and better efficiency (Gong and Caldas, 2008; Blanco et al., 2017; Love and Matthews, 2019) and eliminates the problems associated with codification of construction information (Soman and Whyte, 2020).

Real-time data has a great potential for improving productivity and safety at construction sites (Dave *et al.*, 2016; Soman, Raphael, and Varghese, 2017; Chen and Lu, 2018; Hasan *et al.*, 2019). In this paper, we focus on Scan versus BIM for generating real-time data. Scan-vs-BIM (Scan-versus-BIM) generates an as-built or as-is BIM by comparing an existing BIM to as-built or as-is point cloud data, usually obtained either from Simultaneous Location and Mapping (SLAM) devices, laser scans directly or via 3D reconstruction from photographs. Scanning for point cloud data has become easier with mobile devices' proliferation with 3D scanning capabilities (Senthilvel, Soman, and Varghese, 2017; Otero *et al.*, 2020). Further, edge computing (Khan et al., 2019) has enabled efficient and faster processing for creating as-built data (Ali, Hashemifar, and Dantu, 2020). These developments provide a great foundation for implementing real-time scan versus BIM in construction.

In this paper, we focus on providing a review of the state-of-the-art in real-time scan-vs-BIM technologies. This paper contributes to the existing literature that focuses on applying computer vision for construction by providing the methods, applications, and challenges of using real-time Scan-vs-BIM in construction. The rest of this paper is structured as follows. The background section would give an overview of the data collection methods and representation and the current approaches towards Scan-vs-BIM and their limitations in real-time applications. Methods section would provide the algorithms for enabling real-time Scan-vs-BIM in the context of real-time registration, point matching, pose estimation, etc. The application section offers a set of applications for then real-time Scan-vs-BIM in construction, and the challenges provide the current difficulties in enabling real-time Scan-vs-BIM. Conclusions are presented in the final section, and directions for future research are described in that section.

BACKGROUND

Data collection and representations

Scan-vs-BIM requires a 3D point cloud, ideally supplemented by per-point surface normals and RGB values, acquired by laser scanning or 3D reconstruction from 2D or 2.5D images.

Laser Scanning

Laser scanning techniques include terrestrial, mobile, and aerial laser scanning (Wang, Tan, and Mei, 2020). Portable systems that use a person manually operated trolley or terrestrial robot as a platform and aerial systems mounted on an Unmanned Aerial Vehicle (UAV) are most suitable for real-time data collection purposes. Both systems involve additional sensors to determine the position and orientation of the scanner, e.g., a GPS (Global Positioning System), IMU (Inertial Measurement Unit), or cameras for visual localization via SLAM (Simultaneous Localization and Mapping) (Thomson *et al.*, 2013). To register multiple point clouds from separate laser scans within the same coordinate system, a two-step coarse- and fine registration process is necessary (Pătrăucean *et al.*, 2015; Wang, Tan, and Mei, 2020). Coarse registration extracts an initial transformation matrix for two overlapping point clouds by detecting and matching local features (Guo *et al.*, 2014). Fine registration optimizes the alignment, usually with a variant of the Iterative Closest Point (ICP) algorithm. Registration of point clouds acquired from mobile and aerial systems can be SLAM-driven (Kim, Chen, and Cho, 2018) or performed with real-time variants of ICP (Pomerleau, Colas and Siegwart, 2015).

3D Reconstruction from 2D or 2.5D image data

3D reconstruction is used to retrieve coherent 3D scene information, e.g., point clouds or surfaces, from a set of 2D (RGB) or 2.5D (RGB-D) images. Necessary sub-tasks are registration and fusion, i.e., the combination of information from multiple images or frames into a single representation without redundancy. For 2D (RGB) images, registration is performed by using Structure-from-Motion to obtain camera poses, followed by Multi-View Stereo for dense surface reconstruction (Musialski *et al.*, 2013; Han and Golparvar-Fard, 2015). Fusion is solved inherently through triangulation. For 2.5D (RGB-D) images, the registration process resembles the two-step mentioned above process of coarse- and fine registration, as depth maps are generally converted to point clouds: Adjacent images coarsely aligned, by detecting and matching local features, followed by pairwise registration using ICP and a subsequent global registration, i.e., loop closure (Zanuttigh *et al.*, 2016). SLAM techniques perform registration, fusion, and 3D reconstruction simultaneously and in real-time. KinectFusion (Newcombe *et al.*, 2011) is a popular approach that employs volumetric fusion, as first described by Curless and Levoy (Curless and Levoy, 1996), using a truncated signed distance function (TSDF) within a discrete, volumetric scene representation, i.e., a voxel-grid, to represent the reconstructed surface. The fused TSDF can be obtained by merely updating a weighted running average of accumulated TSDF voxel values every time a new view is added. Since the TSDF is an implicit surface representation, an explicit representation can be extracted by computing its zero-crossings. (Newcombe *et al.*, 2011) uses ray-casting to visualize the surface model.

Indoor Mobile Mapping Systems

Mobile systems for indoor data collection based on 2D or 3D laser scanners or use 3D reconstruction techniques based on RGB or RGB-D sensors are called Indoor Mobile Mapping Systems (IMMS) (Tucci *et al.*, 2018). Although terrestrial laser scanning still provides the most accurate measurements (Otero *et al.*, 2020), IMMS allows for much faster data acquisition of large facilities (Lehtola *et al.*, 2017). Furthermore, certain devices, e.g., handheld or robot mounted devices, enable mapping difficult to access areas, such as crouch-spaces and MEP installations. Compared to terrestrial laser scanners, which achieve survey-grade measurement accuracy of 0.3 to 2mm, IMMS systems commonly provide measurement accuracy between 1 to 5 cm (Otero *et al.*, 2020).

The data acquisition speed and the accuracy, density, and noise of the resulting point cloud vary significantly between different Indoor Mobile Mapping Systems (IMMS). Furthermore, the quality of the resulting point cloud is also influenced by factors relating to the specific device's operation, e.g., walking speed, hand movements (for handheld devices), and sudden turns while walking (Tucci *et al.*, 2018). IMMS with 3D Lidar sensors based on wheeled platforms has been among the systems producing the most accurate point clouds. Although these devices mitigate operative mistakes, such as vertical hand or body movements or sudden turns while walking, they introduce the added limitation that data collection is mostly limited to flat surfaces (Lehtola *et al.*, 2017). Recently, handheld devices using 2D Lidar sensors have achieved even higher mean accuracies (Otero *et al.*, 2020).

Current approaches to Scan-vs-BIM

Scan-vs-BIM approaches can be distinguished depending on whether they utilize point clouds or intermediary image data for BIM object recognition, i.e., to verify the presence or absence of BIM objects in a point cloud.

Object recognition from point cloud data

Approaches of the first kind usually perform (1) registration of point cloud and 3D BIM data, (2) point cloud segmentation by matching individual points to BIM objects, and (3) object recognition from segmented points. Point to BIM object matching generally uses point-to-plane distance metrics. Subsequent object recognition uses metrics based on either the absolute number of matched points (Son and Kim, 2010; Zhang and Arditi, 2013) or the object surface area covered by matched points.

Surface coverage metrics for object recognition are often employed with the goal of invariance towards point cloud density. Bosché et al. introduced and improved a Scan-vs-BIM approach in a series of papers (Bosché and Haas, 2008; Bosché, 2010; Turkan *et al.*, 2012; Bosché *et al.*, 2013) that computes the percentage of recognized surface area in relation to the recognizable surface area, as defined by both self-occlusions and occlusion by other objects. Rebolj et al. (Rebolj *et al.*, 2017) match points to three orthographic surface projections per BIM object and project matched points orthogonally onto the closest plane. Total surface coverage is estimated by rasterizing all three projected surfaces and calculating the surface area of those raster cells that contain points as a percentage of their total surface area. Tran et al. (Tran and Khoshelham, 2019) construct an alpha shape based on the matched points per object surface and calculate the total surface coverage as the sum of the alpha shape surface areas over the total object surface area. Occlusions are not considered.

Object recognition from image data

Instead of or in addition to reconstructed point clouds, Scan-vs-BIM approaches of the second kind register 2D images with 3D BIM data and subsequently back-project BIM semantic information, i.e., instance segmentation, onto the image planes to enable the application of 2D object recognition techniques (Han and Golparvar-Fard, 2015; Han, Degol and Golparvar-Fard, 2018; Kropp, Koch and König, 2018; Braun *et al.*, 2020).

METHODS AND EXTENSIONS FOR REAL-TIME PERFORMANCE

Real-time registration

The registration of 3D BIM information with point cloud data is an essential task for all Scan-vs-BIM approaches. The commonly performed ICP-based fine registration step needs to be run at a sufficiently high frame rate to allow for live visualization: typically, approximately 24 frames per second. ICP iteratively improves the most likely point correspondences. During each iteration, the closest point computation of the basic ICP algorithm has a quadratic complexity ($O(n^2)$) and presents the main bottleneck for real-time performance (Castellani and Bartoli, 2020). Real-time variants of ICP (Castellani and Bartoli, 2020) have been explored for real-time registration of continuously collected point cloud scan data, given that the point clouds are already coarsely pre-aligned, as is the case if for a laser scanner mounted on a mobile platform or held still by a person moving through a building (Pomerleau, Colas, and Siegwart, 2015). However, real-time registration of scanned point cloud data with a complete 3D BIM, or a subset thereof, still presents a significant challenge, especially right after the data collection process has started since an initial rough registration of a small scan with a large model needs to be performed. An initial manual or visual alignment of scanner and BIM, i.e., a known origin pose for the scan, would simplify or make this problem at all feasible. Real-time indoor localization approaches from BIM data, developed for scan planning, could be leveraged for this purpose (Acharya, Khoshelham, and Winter, 2019; Asadi *et al.*, 2019). Further research is necessary to determine the most suitable approach to this problem.

Existing Scan-vs-BIM approaches: Real-time point matching and BIM object recognition

Opportunities and challenges for real-time extensions of the Scan-vs-BIM approach depend on the underlying data representation, i.e., point cloud or RGB/RGB-D image.

Point-cloud-based approaches

Approaches that generate as-designed point clouds from BIM data, e.g., using ray-casting with the same azimuth and elevation angles as a respective terrestrial laser scan (Bosché, 2010), are not easily extendable to real-time performance since the azimuth and elevation angles of a point in relation to an origin position cannot be extracted from the output of an IMMS. IMMS has (1) a scan origin that is continuously in motion and (2) doesn't produce individual, intermediary scans in a standard format that represent individual points in the coordinate system of the scanner and from which their azimuth and elevation angles can hence readily be obtained. Instead, an internal, intermediary representation is used from which a point cloud in a standard exchange format is generated during a post-processing step (Lehtola *et al.*, 2017; Tucci *et al.*, 2018). In formulating the point-to-object matching problem as the task of finding the closest point-to-point or point-to-plane distance, real-time methods developed for registration purposes, e.g., extensions to ICP (Castellani and Bartoli, 2020), could be leveraged. Further research is necessary to identify and apply approaches that extend data association between the point cloud and 3D BIM representations for Scan-vs-BIM towards real-time performance.

Image-based approaches

Scan-vs-BIM approaches that employ 2D object recognition readily lend themselves to extensions for real-time performance, as many mature, real-time 2D object recognition methods are available and can be directly applied. These include deep-learning-based methods, such as lightweight, single-shot object detection models (Redmon and Farhadi, 2017). Lightweight refers to a fast, memory-efficient model, and single-shot describes the process of generating candidate detections in parallel instead of requiring multiple iterations of generating and evaluating candidate detections.

Real-time 3D object detection, pose estimation, and CAD model alignment

For many applications, verifying the presence, completion, or pose of all BIM elements in a given scan is unnecessary. Often the status of specific elements needs to be verified individually. For this purpose, instead of registering the entire 3D BIM with the scanned point cloud upfront, the BIM can be used as a database of 3D CAD models to be detected in and aligned with the scanned point cloud. The task of 3D object detection and pose estimation in RGB or RGB-D images is an established research area in the Computer Vision community. Many solutions exist, including approaches that use 3D CAD models as geometric priors (Lim, Pirsiavash and Torralba, 2013; Sun *et al.*, 2018; Li, Wang, and Ji, 2019; Park, Patten, and Vincze, 2019; Peng *et al.*, 2019; Zakharov, Shugurov and Ilic, 2019; Li *et al.*, 2020) and real-time approaches that are often based on lightweight, single-shot object detection models (Kehl *et al.*, 2017; Redmon and Farhadi, 2017; Tekin, Sinha and Fua, 2018; Hu *et al.*, 2019). Moreover, instead of aligning objects with images, several approaches have been developed to retrieve CAD models from a shape database and align them directly with a 3D scan during data collection in real-time (Kim *et al.*, 2013; Li *et al.*, 2015).
In addition to the above considerations, many method's processing time depends on their hardware and specific application. A virtual reality headset imposes more restrictions on its computing hardware due to its small form factor and proximity to its wearer's skin than a computer mounted on a moveable trolley, for example.

APPLICATIONS

This section provides the potential applications of real-time Scan-vs-BIM applications for use in construction sites. These applications rely on having 3D sensing technologies on the site through stand-alone devices, integrated into augmented reality headsets, mobile devices, or construction robots, as well as a semantically enriched digital information model.

Progress monitoring

The construction phase of projects is dynamic, and activities at the construction site change rapidly, making real-time progress monitoring necessary (Kopsida, Brilakis, and Vela, 2015; Omar and Nehdi, 2016). Although there are various technologies for automated progress monitoring, real-time Scan-vs-BIM offers the advantage that the latest information is visualized and computed simultaneously. Mixed reality has been used as real-time progress monitoring in construction projects (M. Kopsida and Brilakis, 2016; Marianna Kopsida and Brilakis, 2016; Kopsida and Brilakis, 2020). These methods can be combined with constraint-checking frameworks (Soman, Molina-Solana, and Whyte, 2020) to understand the deviations' knock-on effects.

Quality inspections

Quality inspections can be augmented using real-time Scan-vs-BIM. There have been methods developed for marker-less registration into a real environment (M. Kopsida and Brilakis, 2016). Once BIM is registered to the natural environment, real-time Scan-vs-BIM can identify the design model's variations. Prior research has used vision-based methods to detect deviations and defects by comparing a design model with real-world information. (Park *et al.*, 2013; Kwon, Park and Lim, 2014; Zhou, Luo and Yang, 2017). However, these methods use image matching for detecting deviations. Real-time Scan-vs-BIM using 3D data would give a better comparison with design models. Further, these could be used to evaluate real-time clash detection prediction using AR (Salem, Samuel and He, 2020) and machine learning (Hu and Castro-Lacouture, 2019). This could invoke design changes in the model if there are variations between the designed and constructed model.

Safety inspections

Safety inspections are another area where real-time Scan-vs-BIM could make an impact. Prior research has used mobile photogrammetric devices to capture point clouds and then used it to compute safety parameters (Teizer *et al.*, 2017). Augmented reality has been employed to evaluate and do real-time safety checks in construction (Huang, 2020), such as crane navigation (Lin, Petzold, and Hsieh, 2020). Real-time Scan-vs-BIM can further improve the usability of such techniques by comparing the real world with a design model and a set of rules from regulations.

Indoor navigation

Construction robots are becoming more and more pervasive in construction sites. However, robotic navigation in a cluttered environment is a highly computational task. Researchers have sought drones' support to capture 3D data of construction sites (Kim *et al.*, 2019) and reconstructed it to plan optimal routes for robots (Nikoohemat *et al.*, 2020). Vision-based technologies have a great potential to aid indoor navigation (Li, Cheng, and Chen, 2020). Real-time Scan-vs-BIM can further assist these algorithms by providing real-time algorithms (Xu *et al.*, 2020). This is a context of the building by comparing it with the latest semantic information models.

CHALLENGES

Challenges for real-time Scan-vs-BIM approaches arise from (1) the characteristics of mobile data collection systems, e.g., IMMS, and (2) the underlying problems Scan-vs-BIM, i.e., registration and geometry comparison. In the latter context, there are specific challenges for both extending existing Scan-vs-BIM approaches for real-time performance and applying novel 3D object detection, pose estimation and CAD model alignment from the field of Computer Vision to the Construction context.

Data collection

With measurement accuracy between 1 to 5 cm for mobile mapping systems, real-time Scan-vs-BIM approaches are required to handle significantly more deviations between the as-designed and as-built geometries of individuals BIM objects. As the horizontal and vertical scan resolutions of an IMMS can differ dramatically, depending on the device's rotation axis/axes (Tucci *et al.*, 2018), variations in point cloud density need to be considered. Future work needs to compare terrestrial laser scanning with IMMS, both Lidar- and SLAM-based, specifically for indoor Scan-vs-BIM.

Moreover, most IMMS perform point cloud registration as a post-processing step, and no system is currently capable of continuous registration during data collection (Lehtola *et al.*, 2017; Tucci *et al.*, 2018). However, to enable real-time Scan-vs-BIM (or any other real-time application), a mobile mapping system capable of real-time registration, providing a continuously updated mapping of the environment, must be used. Currently, only SLAM systems based on RGB-D sensors can give this kind of real-time data output. It remains to be seen how far IMMS based on 2D and 3D Lidar sensors will be developed to provide this functionality.

Registration and geometry comparison for Scan-vs-BIM

As mentioned above, real-time registration of scan data with a complete 3D BIM, or a subset thereof, still presents a significant challenge. Future research needs to identify or develop real-time fine registration algorithms to register continuously collected scan data in the form of point clouds or mesh models with 3D BIM data. In addition, the problem of the initial rough registration given a small scan with no distinctive features, e.g., a segment of a hallway with plain walls and ceilings or one of many empty rooms, needs to be solved.

Moreover, current point-cloud-based Scan-vs-BIM approaches are not easily extendable for real-time performance, as the real-time methods to perform data association between the point cloud and 3D BIM representations need to be identified. Although image-based Scan-vs-BIM approaches are suitable for real-time extensions, they are currently mostly applied to outdoor applications within the

Civil Engineering community. Further research is necessary to use existing real-time object detection and semantic segmentation models as part of a Scan-vs-BIM system and test it in indoor environments.

Applying novel 3D object detection, pose estimation, and CAD model alignment approaches developed within the Computer Vision community to single-object Scan-vs-BIM problems seems promising for real-time applications. However, these methods have currently only been tested on small sets of small-scale objects, and further research is necessary to evaluate these approaches for comparison with multiple BIM objects or even a complete 3D BIM, containing large scale, featureless, repetitive, and not distinguishable objects, e.g., walls and slabs.

CONCLUSION

Existing methods for Scan-vs-BIM need to be extended to make them suitable for real-time analytics. This paper has presented suggestions for performing registration, point matching, object detection, and pose estimation. This paper contributes to the existing knowledge base on computer vision for construction in several ways. First, this study identifies the limitations of existing methods for Scan-vs-BIM with respect to their real-time performance. Second, this paper addresses these limitations by providing suggestions for extensions to improve their real-time performance. Third, we present the applications for real-time Scan-vs-BIM in construction. Fourth, we have identified the challenges for the implementation of real-time Scan-vs-BIM technologies in construction.

This research study has implications for researchers working in computer vision, augmented reality, and construction robotics. Researchers working in computer vision can use this paper's suggestions to improve their algorithms' real-time performance. Researchers working in augmented reality in construction can consider this paper's recommendations to improve their real-time registration, pose estimation, and BIM alignment methods. Researchers working in construction robotics can use the suggestions presented in this paper for BIM-assisted indoor navigation and indoor localization. There is a potential for research in construction robotics towards developing autonomous robots for construction progress monitoring, quality inspection, and safety inspection.

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